

Load The Dataset (Week 2)

```
In [1]: import pandas as pd
import warnings
warnings.filterwarnings('ignore')
# ingest data
df=pd.read_csv('https://raw.githubusercontent.com/Christine971224/Analytics-2023/master',
df.head()
```

```
Out[1]:
```

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_week_number	arrival
0	Resort Hotel	0	342	2015	July		27
1	Resort Hotel	0	737	2015	July		27
2	Resort Hotel	0	7	2015	July		27
3	Resort Hotel	0	13	2015	July		27
4	Resort Hotel	0	14	2015	July		27

5 rows × 36 columns



```
In [2]: #basic information of dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119390 entries, 0 to 119389
Data columns (total 36 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   hotel                                119390 non-null object
1   is_canceled                          119390 non-null int64
2   lead_time                            119390 non-null int64
3   arrival_date_year                    119390 non-null int64
4   arrival_date_month                   119390 non-null object
5   arrival_date_week_number             119390 non-null int64
6   arrival_date_day_of_month            119390 non-null int64
7   stays_in_weekend_nights              119390 non-null int64
8   stays_in_week_nights                 119390 non-null int64
9   adults                               119390 non-null int64
10  children                             119386 non-null float64
11  babies                               119390 non-null int64
```

12	meal	119390	non-null	object
13	country	118902	non-null	object
14	market_segment	119390	non-null	object
15	distribution_channel	119390	non-null	object
16	is_repeated_guest	119390	non-null	int64
17	previous_cancellations	119390	non-null	int64
18	previous_bookings_not_canceled	119390	non-null	int64
19	reserved_room_type	119390	non-null	object
20	assigned_room_type	119390	non-null	object
21	booking_changes	119390	non-null	int64
22	deposit_type	119390	non-null	object
23	agent	103050	non-null	float64
24	company	6797	non-null	float64
25	days_in_waiting_list	119390	non-null	int64
26	customer_type	119390	non-null	object
27	adr	119390	non-null	float64
28	required_car_parking_spaces	119390	non-null	int64
29	total_of_special_requests	119390	non-null	int64
30	reservation_status	119390	non-null	object
31	reservation_status_date	119390	non-null	object
32	name	119390	non-null	object
33	email	119390	non-null	object
34	phone-number	119390	non-null	object
35	credit_card	119390	non-null	object

dtypes: float64(4), int64(16), object(16)

memory usage: 32.8+ MB

In [3]:

```
# View the proportion of empty values in each column
df.isnull().mean()
```

Out[3]:

hotel	0.000000
is_canceled	0.000000
lead_time	0.000000
arrival_date_year	0.000000
arrival_date_month	0.000000
arrival_date_week_number	0.000000
arrival_date_day_of_month	0.000000
stays_in_weekend_nights	0.000000
stays_in_week_nights	0.000000
adults	0.000000
children	0.000034
babies	0.000000
meal	0.000000
country	0.004087
market_segment	0.000000
distribution_channel	0.000000
is_repeated_guest	0.000000
previous_cancellations	0.000000
previous_bookings_not_canceled	0.000000
reserved_room_type	0.000000
assigned_room_type	0.000000
booking_changes	0.000000
deposit_type	0.000000
agent	0.136862
company	0.943069
days_in_waiting_list	0.000000
customer_type	0.000000
adr	0.000000
required_car_parking_spaces	0.000000

```
total_of_special_requests    0.000000
reservation_status           0.000000
reservation_status_date      0.000000
name                         0.000000
email                        0.000000
phone-number                 0.000000
credit_card                  0.000000
dtype: float64
```

In [4]:

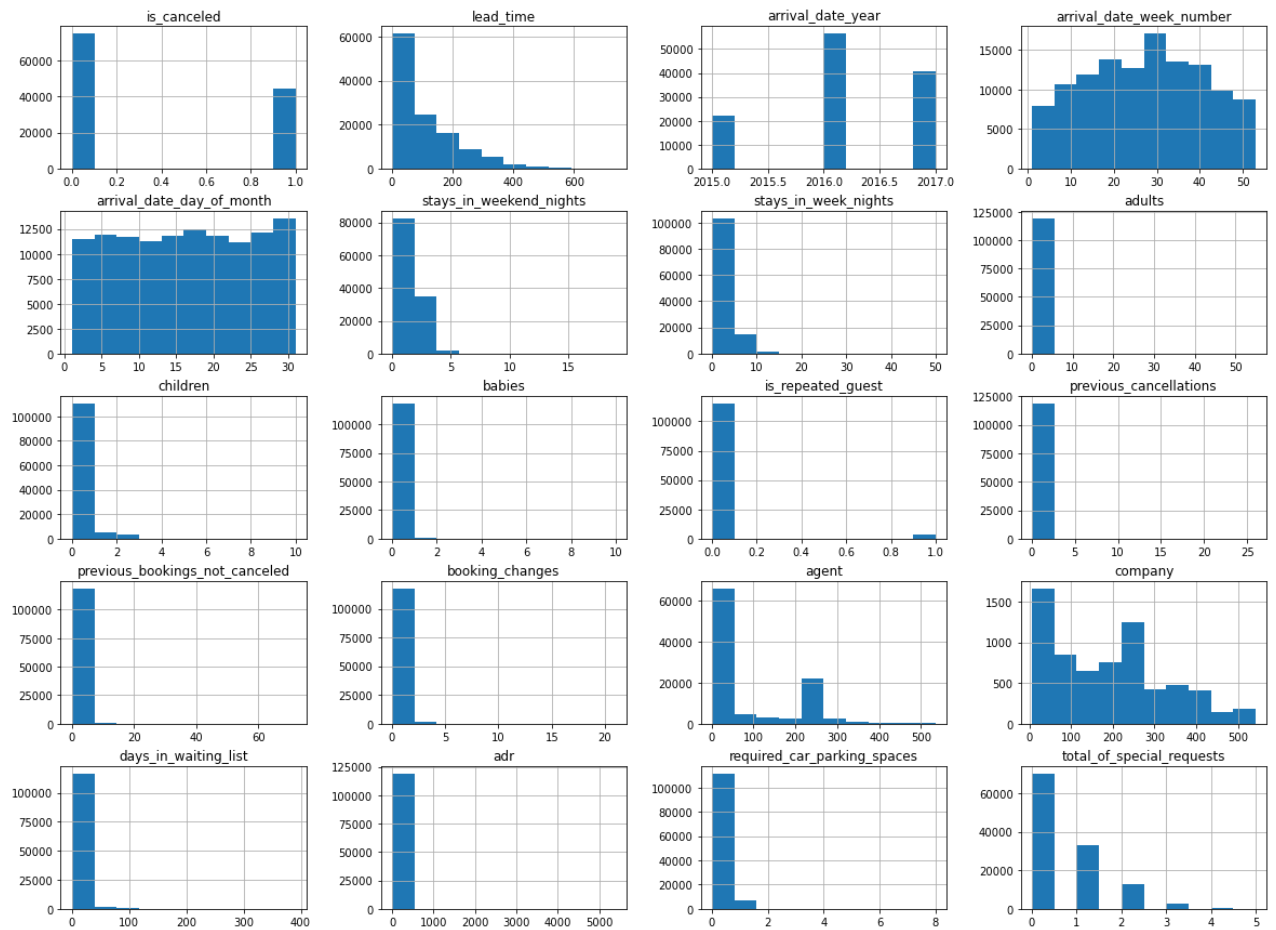
```
# Transpose the resulting DataFrame
df.describe([0.01,0.05,0.1,0.25,0.5,0.75,0.99]).T
```

Out[4]:

	count	mean	std	min	1%	5%	10%	25%
is_canceled	119390.0	0.370416	0.482918	0.00	0.0	0.0	0.0	0.0
lead_time	119390.0	104.011416	106.863097	0.00	0.0	0.0	3.0	18.0
arrival_date_year	119390.0	2016.156554	0.707476	2015.00	2015.0	2015.0	2015.0	2016.0
arrival_date_week_number	119390.0	27.165173	13.605138	1.00	2.0	5.0	8.0	16.0
arrival_date_day_of_month	119390.0	15.798241	8.780829	1.00	1.0	2.0	4.0	8.0
stays_in_weekend_nights	119390.0	0.927599	0.998613	0.00	0.0	0.0	0.0	0.0
stays_in_week_nights	119390.0	2.500302	1.908286	0.00	0.0	0.0	1.0	1.0
adults	119390.0	1.856403	0.579261	0.00	1.0	1.0	1.0	2.0
children	119386.0	0.103890	0.398561	0.00	0.0	0.0	0.0	0.0
babies	119390.0	0.007949	0.097436	0.00	0.0	0.0	0.0	0.0
is_repeated_guest	119390.0	0.031912	0.175767	0.00	0.0	0.0	0.0	0.0
previous_cancellations	119390.0	0.087118	0.844336	0.00	0.0	0.0	0.0	0.0
previous_bookings_not_canceled	119390.0	0.137097	1.497437	0.00	0.0	0.0	0.0	0.0
booking_changes	119390.0	0.221124	0.652306	0.00	0.0	0.0	0.0	0.0
agent	103050.0	86.693382	110.774548	1.00	1.0	1.0	6.0	9.0
company	6797.0	189.266735	131.655015	6.00	16.0	40.0	40.0	62.0
days_in_waiting_list	119390.0	2.321149	17.594721	0.00	0.0	0.0	0.0	0.0
adr	119390.0	101.831122	50.535790	-6.38	0.0	38.4	50.0	69.0
required_car_parking_spaces	119390.0	0.062518	0.245291	0.00	0.0	0.0	0.0	0.0
total_of_special_requests	119390.0	0.571363	0.792798	0.00	0.0	0.0	0.0	0.0

In [5]:

```
import matplotlib.pyplot as plt
# generate histograms for all the columns
df.hist(figsize=(20,15))
plt.show()
```

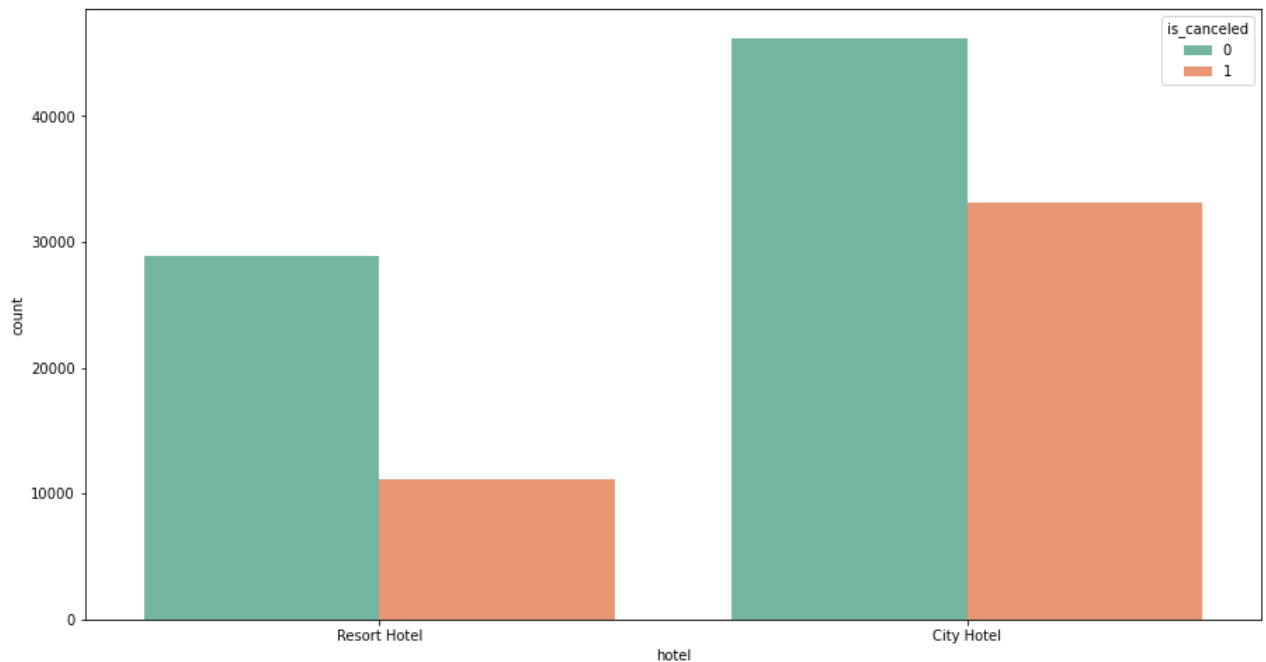


EDA (Week 3)

1. Hotel bookings and cancellations

```
In [6]: # The number of hotel reservations and cancellations can directly show the actual number
import seaborn as sns
plt.figure(figsize=(15,8))
sns.countplot(x='hotel',
              data=df,
              hue='is_canceled',
              palette=sns.color_palette('Set2',2)
              )
```

```
Out[6]: <AxesSubplot:xlabel='hotel', ylabel='count'>
```



In [7]:

```
#calculate the proportion of cancellations for each unique value in the 'hotel' column
hotel_cancel=(df.loc[df['is_canceled']==1]['hotel'].value_counts()/df['hotel'].value_co
print('Hotel cancellations'.center(20),hotel_cancel,sep='\n')
```

```
Hotel cancellations
City Hotel      0.417270
Resort Hotel    0.277634
Name: hotel, dtype: float64
```

Comment: City Hotel's booking volume and cancellation volume are both higher than Resort Hotel's, but Resort Hotel's cancellation rate is 27.8%, while City Hotel's cancellation rate reaches 41.7%.

2. Hotel bookings by month

In [8]:

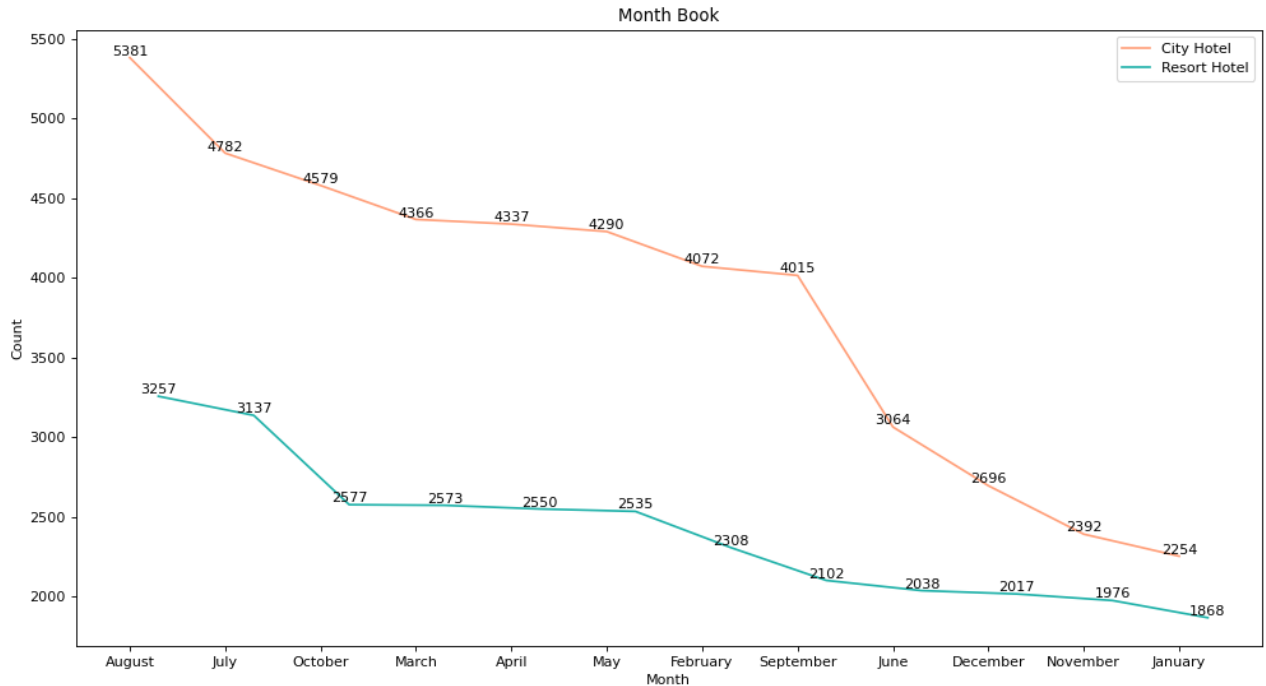
```
#create a plot to visualize the number of bookings for "City Hotel" and "Resort Hotel"
#focusing only on the ones where 'is_canceled' is 0, meaning the bookings that were not
city_hotel=df[(df['hotel']=='City Hotel') & (df['is_canceled']==0)]
resort_hotel=df[(df['hotel']=='Resort Hotel') & (df['is_canceled']==0)]
for i in [city_hotel,resort_hotel]:
    i.index=range(i.shape[0])
```

In [9]:

```
city_month=city_hotel['arrival_date_month'].value_counts()
resort_month=resort_hotel['arrival_date_month'].value_counts()
name=resort_month.index
x=list(range(len(city_month.index)))
y=city_month.values
x1=[i+0.3 for i in x]
y1=resort_month.values
width=0.3
plt.figure(figsize=(15,8),dpi=80)
plt.plot(x,y,label='City Hotel',color='lightsalmon')
plt.plot(x1,y1,label='Resort Hotel',color='lightseagreen')
plt.xticks(x,name)
plt.legend()
```

```
plt.xlabel('Month')
plt.ylabel('Count')
plt.title('Month Book')
for x,y in zip(x,y):
    plt.text(x,y+0.1,'%d' % y,ha = 'center',va = 'bottom')

for x,y in zip(x1,y1):
    plt.text(x,y+0.1,'%d' % y,ha = 'center',va = 'bottom')
```

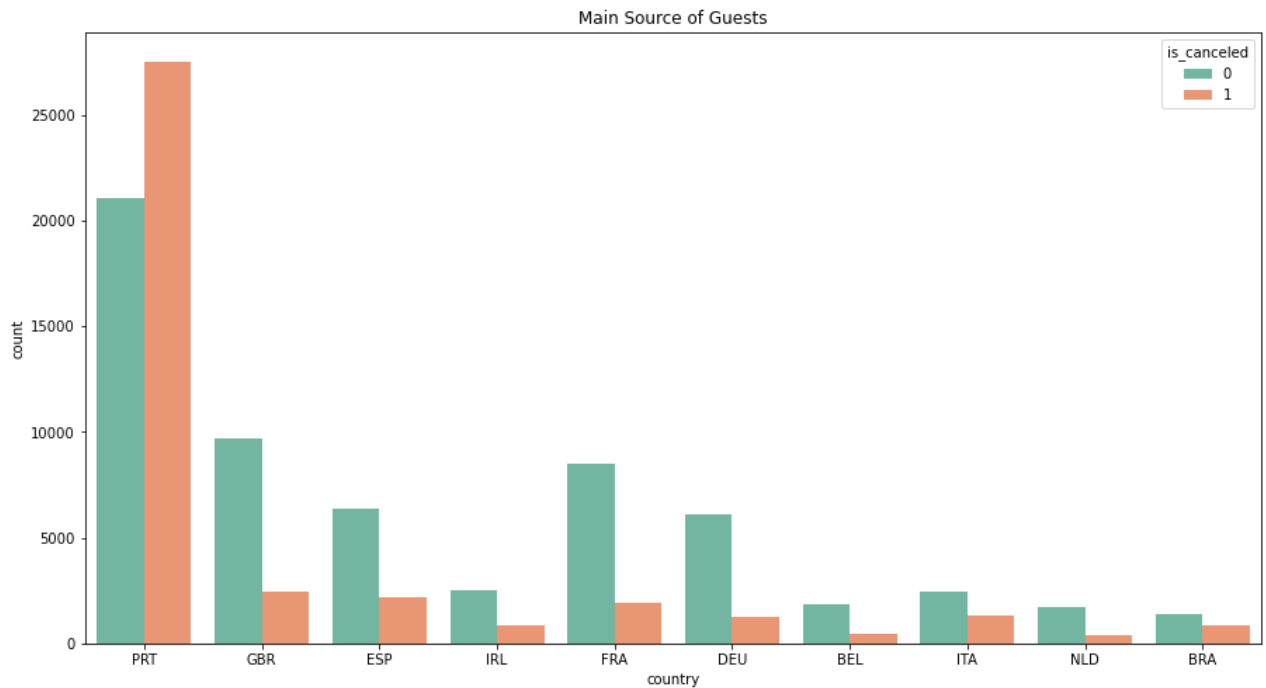


Comment: Peak booking months are August and July. Preliminary judgment is that the long holiday caused the peak period.

3. Customer origin and booking cancellation rate

```
In [10]: #create a plot using Seaborn's countplot to visualize the top 10 countries from which booking
country_book=df['country'].value_counts()[:10]
country_cancel=df[(df.country.isin (country_book.index)) & (df.is_canceled==1)][['country']]
plt.figure(figsize=(15,8))
sns.countplot(x='country',
              data=df[df.country.isin (country_book.index)],
              hue='is_canceled',
              palette=sns.color_palette('Set2',2))
plt.title('Main Source of Guests')
```

```
Out[10]: Text(0.5, 1.0, 'Main Source of Guests')
```



```
In [11]: #calculate the cancellation rate for each of the top 10 countries (those with the highest
country_cancel_rate=(country_cancel/country_book).sort_values(ascending=False)
print('Customer cancellation rates by country'.center(10),country_cancel_rate,sep='\n')
```

Customer cancellation rates by country

```
PRT    0.566351
BRA    0.373201
ITA    0.353956
ESP    0.254085
IRL    0.246519
BEL    0.202391
GBR    0.202243
FRA    0.185694
NLD    0.183935
DEU    0.167147
```

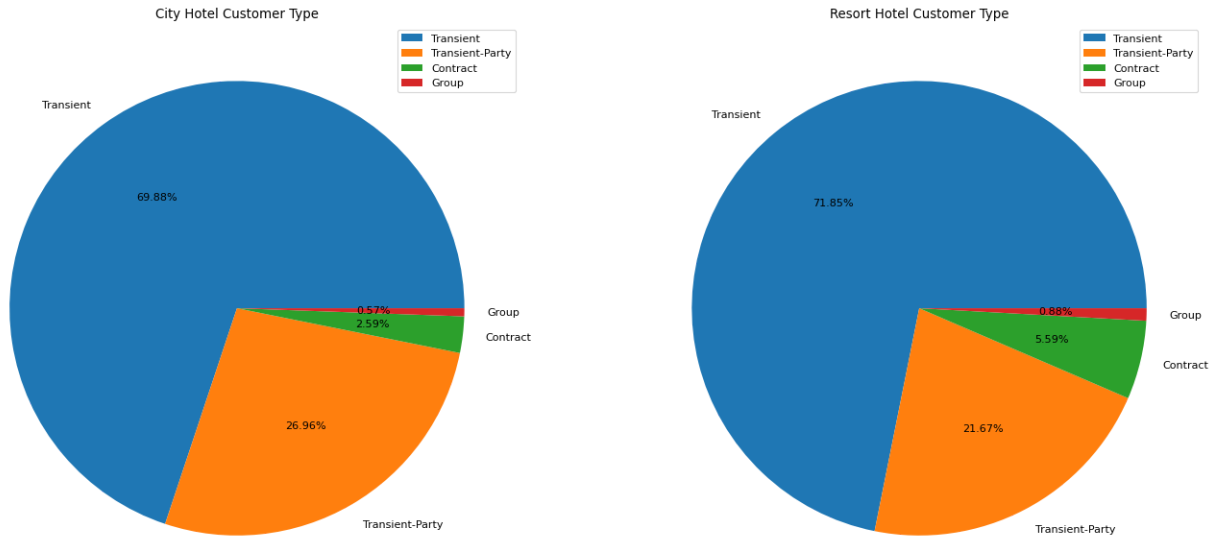
Name: country, dtype: float64

The peak season for both Resort hotel and City hotel is July and August in summer, and the main sources of tourists are European countries. This is in line with the characteristics of European tourists who prefer summer travel. It is necessary to focus on countries with high cancellation rates such as Portugal (PRT) and the United Kingdom (BRT). Main source of customers.

4. Customer type

```
In [12]: #visualize the distribution of customer types for two types of hotels: City Hotel and Resort
city_customer=city_hotel.customer_type.value_counts()
resort_customer=resort_hotel.customer_type.value_counts()
plt.figure(figsize=(21,12),dpi=80)
plt.subplot(1,2,1)
plt.pie(city_customer,labels=city_customer.index,autopct='%0.2f%%')
plt.legend(loc=1)
plt.title('City Hotel Customer Type')
plt.subplot(1,2,2)
plt.pie(resort_customer,labels=resort_customer.index,autopct='%0.2f%%')
```

```
plt.title('Resort Hotel Customer Type')
plt.legend()
plt.show()
```

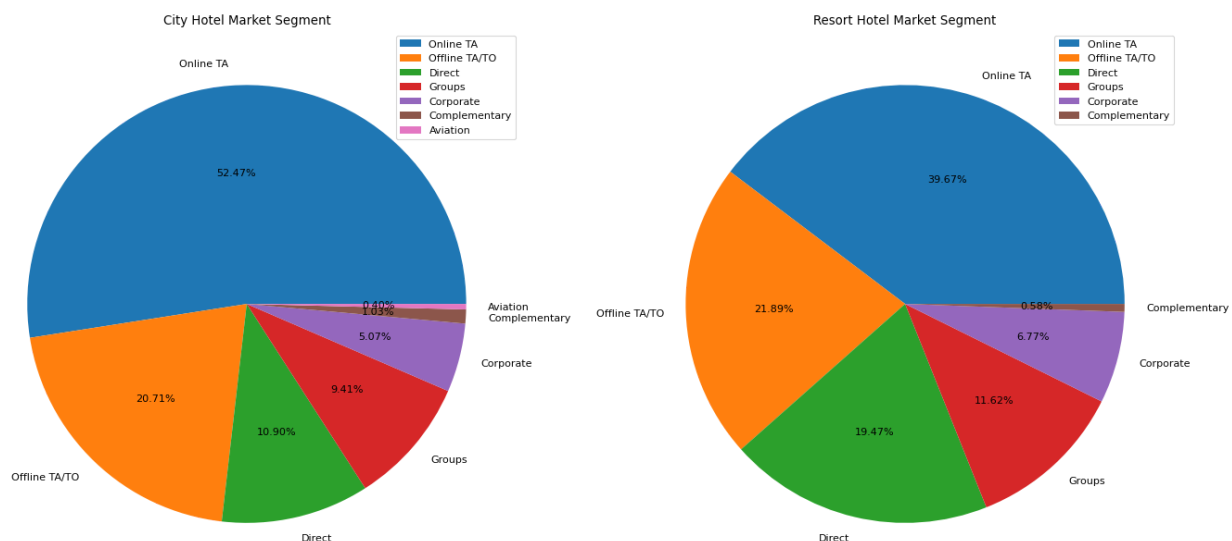


The main customer type of the hotel is transient travelers, accounting for about 70%.

5. Hotel booking method

In [13]:

```
#create pie charts to visualize the distribution of market segments for both City Hotel
city_segment=city_hotel.market_segment.value_counts()
resort_segment=resort_hotel.market_segment.value_counts()
plt.figure(figsize=(21,12),dpi=80)
plt.subplot(1,2,1)
plt.pie(city_segment,labels=city_segment.index,autopct='%.2f%')
plt.legend()
plt.title('City Hotel Market Segment')
plt.subplot(1,2,2)
plt.pie(resort_segment,labels=resort_segment.index,autopct='%.2f%')
plt.title('Resort Hotel Market Segment')
plt.legend()
plt.show()
```

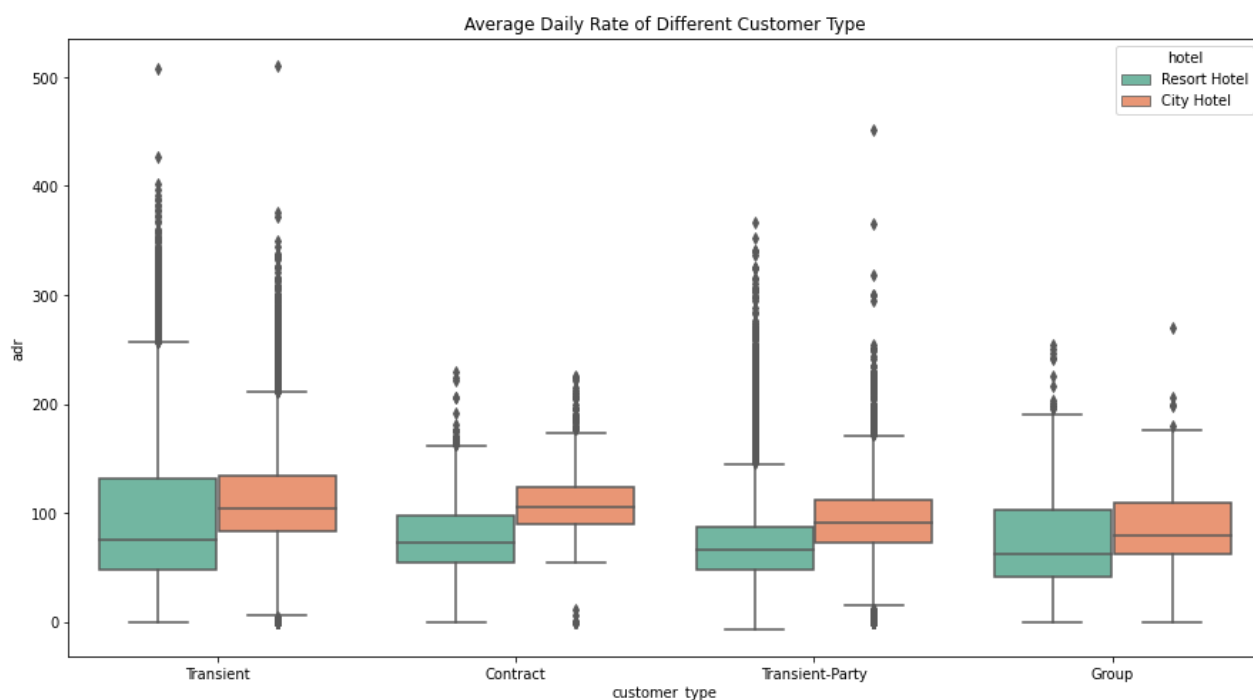



The customers of the two hotels mainly come from online travel agencies, which account for even more than 50% of the City Hotel; offline travel agencies come next, accounting for about 20%.

6. Average daily expenses of various types of passengers

```
In [14]: #visualize the distribution of Average Daily Rate (adr) across different customer types.
plt.figure(figsize=(15,8))
sns.boxplot(x='customer_type',
            y='adr',
            hue='hotel',
            data=df[df.is_canceled==0],
            palette=sns.color_palette('Set2',2))
plt.title('Average Daily Rate of Different Customer Type')
```

```
Out[14]: Text(0.5, 1.0, 'Average Daily Rate of Different Customer Type')
```

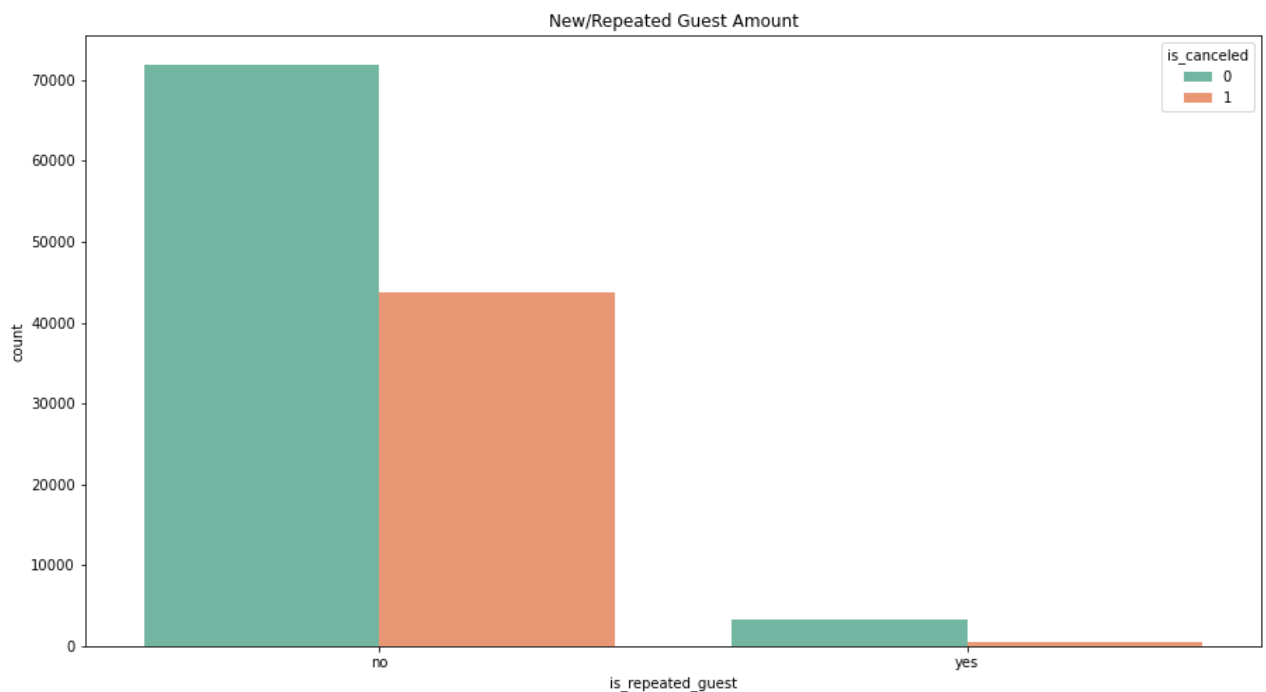


The average daily expenditure of all types of customers of City Hotel is higher than that of Resort Hotel; among the four types of customers, the consumption of individual travelers (Transient) is the highest and that of group travelers (Group) is the lowest.

7. Number of new and old customers and cancellation rate

```
In [15]: # visualize the count of bookings, categorized by whether the guest is a repeated guest
plt.figure(figsize=(15,8))
sns.countplot(x='is_repeated_guest'
              ,data=df
              ,hue='is_canceled'
              ,palette=sns.color_palette('Set2',2)
              )
plt.title('New/Repeated Guest Amount')
plt.xticks(range(2),['no','yes'])
```

```
Out[15]: ([<matplotlib.axis.XTick at 0x224c62d5700>,
<matplotlib.axis.XTick at 0x224c62d56d0>],
[Text(0, 0, 'no'), Text(1, 0, 'yes')])
```



```
In [16]: #calculate and printing the cancellation rates for new and repeated guests
guest_cancel=(df.loc[df['is_canceled']==1]['is_repeated_guest'].value_counts()/df['is_repeated_guest'].value_counts())
guest_cancel.index=['New Guest', 'Repeated Guest']
print('Cancellation rate for new and old customers'.center(15),guest_cancel,sep='\n')
```

```
Cancellation rate for new and old customers
New Guest      0.377851
Repeated Guest  0.144882
Name: is_repeated_guest, dtype: float64
```

The cancellation rate for regular customers was 14.4%, while the cancellation rate for new customers reached 37.8%, which was 24 percentage points higher than that for regular customers.

8. Deposit method and reservation cancellation rate

In [17]: `print('Three deposit methods for booking quantity'.center(15),df['deposit_type'].value_`

Three deposit methods for booking quantity

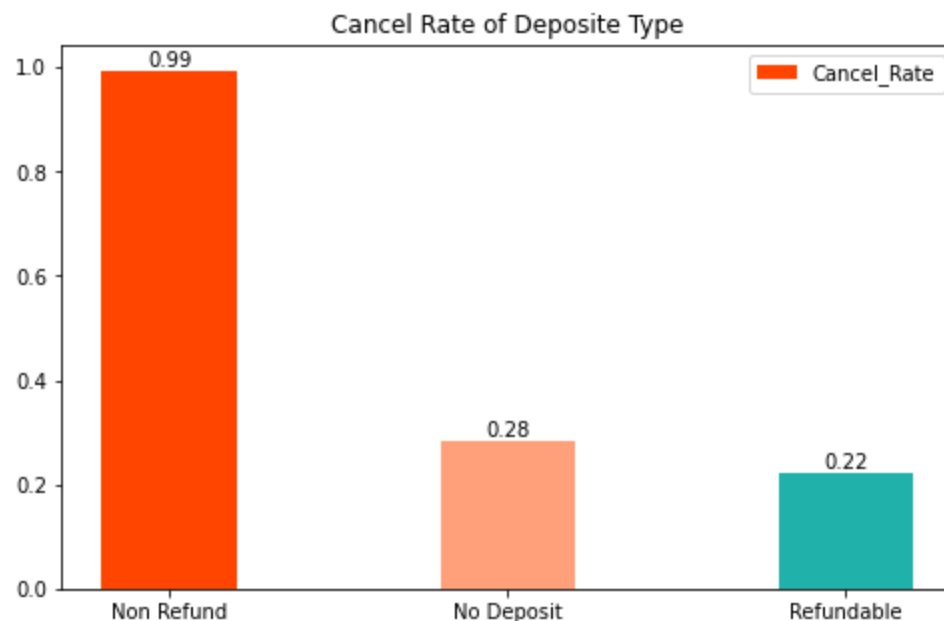
No Deposit 104641

Non Refund 14587

Refundable 162

Name: deposit_type, dtype: int64

In [18]: `#calculate the cancellation rates based on the 'deposit_type', and visualizing these rates
deposit_cancel=(df.loc[df['is_canceled']==1]['deposit_type'].value_counts()/df['deposit_type'].value_counts())
plt.figure(figsize=(8,5))
x=range(len(deposit_cancel.index))
y=deposit_cancel.values
plt.bar(x,y,label='Cancel_Rate',color=['orangered','lightsalmon','lightseagreen'],width=0.5)
plt.xticks(x,deposit_cancel.index)
plt.legend()
plt.title('Cancel Rate of Deposit Type')
for x,y in zip(x,y):
 plt.text(x,y,'%.2f' % y,ha = 'center',va = 'bottom')`



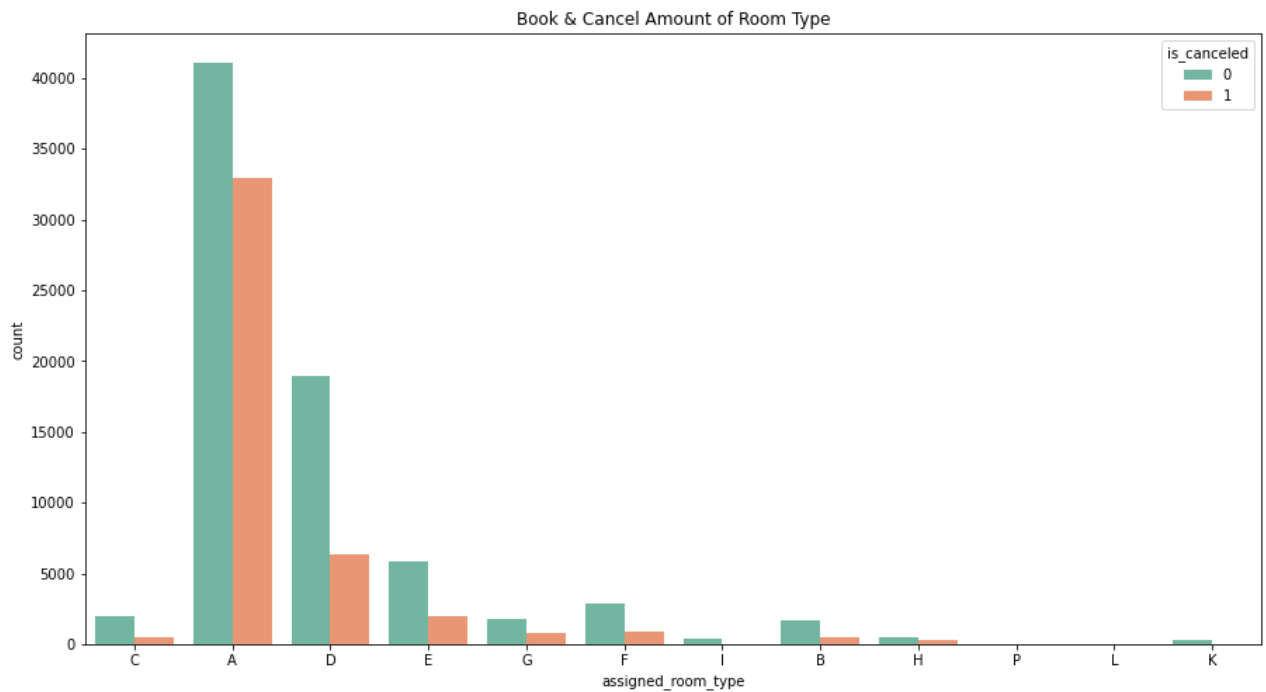
'No Deposit' is the method with the highest number of bookings and has a low cancellation rate, while the cancellation rate of non-refundable type is as high as 99%. This type of deposit method can be reduced to reduce Customer cancellation rate.

9. Room type and cancellation volume

In [19]: `#visualize the counts of bookings and cancellations across different assigned room types
plt.figure(figsize=(15,8))
sns.countplot(x='assigned_room_type',
 data=df,
 hue='is_canceled',
 palette=sns.color_palette('Set2',2))`

```
)
plt.title('Book & Cancel Amount of Room Type')
```

Out[19]: Text(0.5, 1.0, 'Book & Cancel Amount of Room Type')



```
In [20]: room_cancel=df.loc[df['is_canceled']==1]['assigned_room_type'].value_counts()[:7]/df['a
print('Cancellation rates for different room types'.center(5),room_cancel.sort_values(a
```

Cancellation rates for different room types

```
A    0.444925
G    0.305523
E    0.252114
D    0.251244
F    0.247134
B    0.236708
C    0.187789
```

Name: assigned_room_type, dtype: float64

Among the top seven room types with the most bookings, the cancellation rates of room types A and G are higher than other room types, and the cancellation rate of room type A is as high as 44.5%.

10. Conclusion

1. The booking volume and cancellation rate of City Hotel are much higher than that of Resort Hotel. The hotel should conduct customer surveys to gain an in-depth understanding of the factors that cause customers to give up on bookings in order to reduce customer cancellation rates.
2. Hotels should make good use of the peak tourist season of July and August every year. They can increase prices appropriately while ensuring service quality to obtain more profits, and

- conduct preferential activities during the off-season (winter), such as Christmas sales and New Year activities, to reduce Hotel vacancy rate.
- Hotels need to analyze customer profiles from major source countries such as Portugal and the United Kingdom, understand the attribute tags, preferences and consumption characteristics of these customers, and launch exclusive services to reduce customer cancellation rates.
 - Since individual travelers are the main customer group of hotels and have high consumption levels, hotels can increase the promotion and marketing of independent travelers through online and offline travel agencies, thereby attracting more tourists of this type.
 - The cancellation rate of new customers is 24% higher than that of old customers. Therefore, hotels should focus on the booking and check-in experience of new customers, and provide more guidance and benefits to new customers, such as providing discounts to first-time customers and conducting research on new customers. Provide feedback on satisfaction and dissatisfaction with your stay to improve future services and maintain good old customers.
 - The cancellation rate of non-refundable deposits is as high as 99%. Hotels should optimize this method, such as returning 50% of the deposit, or cancel this method directly to increase the occupancy rate.
 - The cancellation rate of room types A and G is much higher than that of other room types. The hotel should carefully confirm the room information with the customer when making a reservation, so that the customer can fully understand the room situation, avoid cognitive errors, and at the same time be able to understand the room facilities. Optimize and improve service levels.

Data Processing (Week 4)

The purpose of modeling is to predict whether a passenger will cancel a hotel reservation, and then set 'is_canceled' to label y, and the rest to feature x. The date feature 'is_canceled_reservation_status_date' does not directly affect the label, so remove it

```
In [21]: #Create a new DataFrame 'df1' from 'df'
df1=df.drop(labels=['reservation_status_date'],axis=1)
```

Handling Categorical Variables

```
In [22]: #Getting the names of all columns in 'df1'
cate=df1.columns[df1.dtypes == "object"].tolist()
#Categorical variables expressed as numbers
num_cate=['agent','company','is_repeated_guest']
cate=cate+num_cate
```

```
In [23]: import numpy as np #linear algebra
#creating a dictionary
results={}
for i in ['agent','company']:
```

```

result=np.sort(df1[i].unique())
results[i]=result
results

```

```

Out[23]: {'agent': array([ 1.,  2.,  3.,  4.,  5.,  6.,  7.,  8.,  9., 10., 11.,
    12., 13., 14., 15., 16., 17., 19., 20., 21., 22., 23.,
    24., 25., 26., 27., 28., 29., 30., 31., 32., 33., 34.,
    35., 36., 37., 38., 39., 40., 41., 42., 44., 45., 47.,
    50., 52., 53., 54., 55., 56., 57., 58., 59., 60., 61.,
    63., 64., 66., 67., 68., 69., 70., 71., 72., 73., 74.,
    75., 77., 78., 79., 81., 82., 83., 85., 86., 87., 88.,
    89., 90., 91., 92., 93., 94., 95., 96., 98., 99., 103.,
    104., 105., 106., 107., 110., 111., 112., 114., 115., 117., 118.,
    119., 121., 122., 126., 127., 128., 129., 132., 133., 134., 135.,
    138., 139., 141., 142., 143., 144., 146., 147., 148., 149., 150.,
    151., 152., 153., 154., 155., 156., 157., 158., 159., 162., 163.,
    165., 167., 168., 170., 171., 173., 174., 175., 177., 179., 180.,
    181., 182., 183., 184., 185., 187., 191., 192., 193., 195., 196.,
    197., 201., 205., 208., 210., 211., 213., 214., 215., 216., 219.,
    220., 223., 227., 229., 232., 234., 235., 236., 240., 241., 242.,
    243., 244., 245., 247., 248., 249., 250., 251., 252., 253., 254.,
    256., 257., 258., 261., 262., 265., 267., 269., 270., 273., 275.,
    276., 278., 280., 281., 282., 283., 285., 286., 287., 288., 289.,
    290., 291., 294., 295., 296., 298., 299., 300., 301., 302., 303.,
    304., 305., 306., 307., 308., 310., 313., 314., 315., 321., 323.,
    324., 325., 326., 327., 328., 330., 331., 332., 333., 334., 335.,
    336., 337., 339., 341., 344., 346., 348., 350., 352., 354., 355.,
    358., 359., 360., 363., 364., 367., 368., 370., 371., 375., 378.,
    384., 385., 387., 388., 390., 391., 393., 394., 397., 403., 404.,
    405., 406., 408., 410., 411., 414., 416., 418., 420., 423., 425.,
    426., 427., 429., 430., 431., 432., 433., 434., 436., 438., 440.,
    441., 444., 446., 449., 450., 451., 453., 454., 455., 459., 461.,
    464., 467., 468., 469., 472., 474., 475., 476., 479., 480., 481.,
    483., 484., 492., 493., 495., 497., 502., 508., 509., 510., 526.,
    527., 531., 535., nan]),
  'company': array([ 6.,  8.,  9., 10., 11., 12., 14., 16., 18., 20., 22.,
    28., 29., 31., 32., 34., 35., 37., 38., 39., 40., 42.,
    43., 45., 46., 47., 48., 49., 51., 52., 53., 54., 59.,
    61., 62., 64., 65., 67., 68., 71., 72., 73., 76., 77.,
    78., 80., 81., 82., 83., 84., 85., 86., 88., 91., 92.,
    93., 94., 96., 99., 100., 101., 102., 103., 104., 105., 106.,
    107., 108., 109., 110., 112., 113., 115., 116., 118., 120., 122.,
    126., 127., 130., 132., 135., 137., 139., 140., 142., 143., 144.,
    146., 148., 149., 150., 153., 154., 158., 159., 160., 163., 165.,
    167., 168., 169., 174., 178., 179., 180., 183., 184., 185., 186.,
    192., 193., 195., 197., 200., 202., 203., 204., 207., 209., 210.,
    212., 213., 215., 216., 217., 218., 219., 220., 221., 222., 223.,
    224., 225., 227., 229., 230., 232., 233., 234., 237., 238., 240.,
    242., 243., 245., 246., 250., 251., 253., 254., 255., 257., 258.,
    259., 260., 263., 264., 268., 269., 270., 271., 272., 273., 274.,
    275., 277., 278., 279., 280., 281., 282., 284., 286., 287., 288.,
    289., 290., 291., 292., 293., 297., 301., 302., 304., 305., 307.,
    308., 309., 311., 312., 313., 314., 316., 317., 318., 319., 320.,
    321., 323., 324., 325., 329., 330., 331., 332., 333., 334., 337.,
    338., 341., 342., 343., 346., 347., 348., 349., 350., 351., 352.,
    353., 355., 356., 357., 358., 360., 361., 362., 364., 365., 366.,
    367., 368., 369., 370., 371., 372., 373., 376., 377., 378., 379.,
    380., 382., 383., 384., 385., 386., 388., 390., 391., 392., 393.,
    394., 395., 396., 397., 398., 399., 400., 401., 402., 403., 405.,
    407., 408., 409., 410., 411., 412., 413., 415., 416., 417., 418.,

```

```
419., 420., 421., 422., 423., 424., 425., 426., 428., 429., 433.,
435., 436., 437., 439., 442., 443., 444., 445., 446., 447., 448.,
450., 451., 452., 454., 455., 456., 457., 458., 459., 460., 461.,
465., 466., 470., 477., 478., 479., 481., 482., 483., 484., 485.,
486., 487., 489., 490., 491., 492., 494., 496., 497., 498., 499.,
501., 504., 506., 507., 511., 512., 513., 514., 515., 516., 518.,
520., 521., 523., 525., 528., 530., 531., 534., 539., 541., 543.,
nan]}}
```

```
In [24]: # the agent and company columns have a large number of empty values and no 0 values, so
df1[['agent', 'company']] = df1[['agent', 'company']].fillna(0, axis=0)
```

```
In [25]: df1.loc[:, cate].isnull().mean()
```

```
Out[25]: hotel                0.000000
arrival_date_month          0.000000
meal                       0.000000
country                    0.004087
market_segment              0.000000
distribution_channel         0.000000
reserved_room_type          0.000000
assigned_room_type          0.000000
deposit_type                0.000000
customer_type               0.000000
reservation_status          0.000000
name                       0.000000
email                      0.000000
phone-number                0.000000
credit_card                 0.000000
agent                      0.000000
company                    0.000000
is_repeated_guest           0.000000
dtype: float64
```

```
In [26]: #create new variables in_company and in_agent to classify passengers. If company and agent are not 0, then they are in the company or agent.
df1.loc[df1['company'] == 0, 'in_company'] = 'NO'
df1.loc[df1['company'] != 0, 'in_company'] = 'YES'
df1.loc[df1['agent'] == 0, 'in_agent'] = 'NO'
df1.loc[df1['agent'] != 0, 'in_agent'] = 'YES'
```

```
In [27]: #create a new feature same_assignment. If the booked room type is consistent with the assigned room type, then it is a same assignment.
df1.loc[df1['reserved_room_type'] == df1['assigned_room_type'], 'same_assignment'] = 'Yes'
df1.loc[df1['reserved_room_type'] != df1['assigned_room_type'], 'same_assignment'] = 'No'
```

```
In [28]: #delete four features except 'reserved_room_type', 'assigned_room_type', 'agent', 'company'
df1 = df1.drop(labels=['reserved_room_type', 'assigned_room_type', 'agent', 'company'], axis=1)
```

```
In [29]: #reset 'is_repeated_guest', frequent guests are marked as YES, non-repeated guests are marked as NO
df1['is_repeated_guest'][df1['is_repeated_guest'] == 0] = 'NO'
df1['is_repeated_guest'][df1['is_repeated_guest'] == 1] = 'YES'
```

```
In [30]: #filling the missing values in the 'country' column of the DataFrame 'df1' with the mode
df1['country']=df1['country'].fillna(df1['country'].mode()[0])
```

```
In [31]: for i in ['in_company','in_agent','same_assignment']:
        cate.append(i)

        for i in ['reserved_room_type','assigned_room_type','agent','company']:
            cate.remove(i)
        cate
```

```
Out[31]: ['hotel',
'arrival_date_month',
'meal',
'country',
'market_segment',
'distribution_channel',
'deposit_type',
'customer_type',
'reservation_status',
'name',
'email',
'phone-number',
'credit_card',
'is_repeated_guest',
'in_company',
'in_agent',
'same_assignment']
```

```
In [32]: #encoding categorical features
from sklearn.preprocessing import OrdinalEncoder
oe = OrdinalEncoder()
oe = oe.fit(df1.loc[:,cate])
df1.loc[:,cate] = oe.transform(df1.loc[:,cate])
```

Working With Continuous Variables

```
In [33]: #to filter out continuous variables, you need to delete the label 'is_canceled' first.
col=df1.columns.tolist()
col.remove('is_canceled')
for i in cate:
    col.remove(i)
col
```

```
Out[33]: ['lead_time',
'arrival_date_year',
'arrival_date_week_number',
'arrival_date_day_of_month',
'stays_in_weekend_nights',
'stays_in_week_nights',
'adults',
'children',
'babies',
'previous_cancellations',
'previous_bookings_not_canceled',
'booking_changes',
```



```
'days_in_waiting_list',
'adr',
'required_car_parking_spaces',
'total_of_special_requests']
```

```
In [34]: df1[col].isnull().sum()
```

```
Out[34]: lead_time                0
arrival_date_year                0
arrival_date_week_number        0
arrival_date_day_of_month       0
stays_in_weekend_nights         0
stays_in_week_nights            0
adults                          0
children                        4
babies                          0
previous_cancellations          0
previous_bookings_not_canceled  0
booking_changes                 0
days_in_waiting_list           0
adr                             0
required_car_parking_spaces     0
total_of_special_requests       0
dtype: int64
```

```
In [35]: #use mode to fill null values in xtrain children column
df1['children']=df1['children'].fillna(df1['children'].mode()[0])
```

```
In [36]: #continuous variables are dimensionless
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
ss = ss.fit(df1.loc[:,col])
df1.loc[:,col] = ss.transform(df1.loc[:,col])
```

Correlation Coefficient of Each Variable

```
In [37]: #calculating the correlation of all numerical columns with the 'is_canceled column' in
cor=df1.corr()
cor=abs(cor['is_canceled']).sort_values()
cor
```

```
Out[37]: email                0.000723
arrival_date_month           0.001491
stays_in_weekend_nights     0.001791
credit_card                  0.002515
name                        0.004253
phone-number                 0.004342
children                     0.005036
arrival_date_day_of_month    0.006130
arrival_date_week_number     0.008148
arrival_date_year            0.016660
meal                        0.017678
stays_in_week_nights        0.024765
babies                       0.032491
adr                          0.047557
```

```

days_in_waiting_list      0.054186
previous_bookings_not_canceled 0.057358
market_segment            0.059338
adults                    0.060017
customer_type              0.068140
is_repeated_guest          0.084793
in_company                 0.099310
in_agent                   0.102068
previous_cancellations     0.110133
hotel                     0.136531
booking_changes            0.144381
distribution_channel        0.167600
required_car_parking_spaces 0.195498
total_of_special_requests  0.234658
same_assignment            0.247770
country                    0.267502
lead_time                  0.293123
deposit_type               0.468634
reservation_status         0.917196
is_canceled                1.000000
Name: is_canceled, dtype: float64

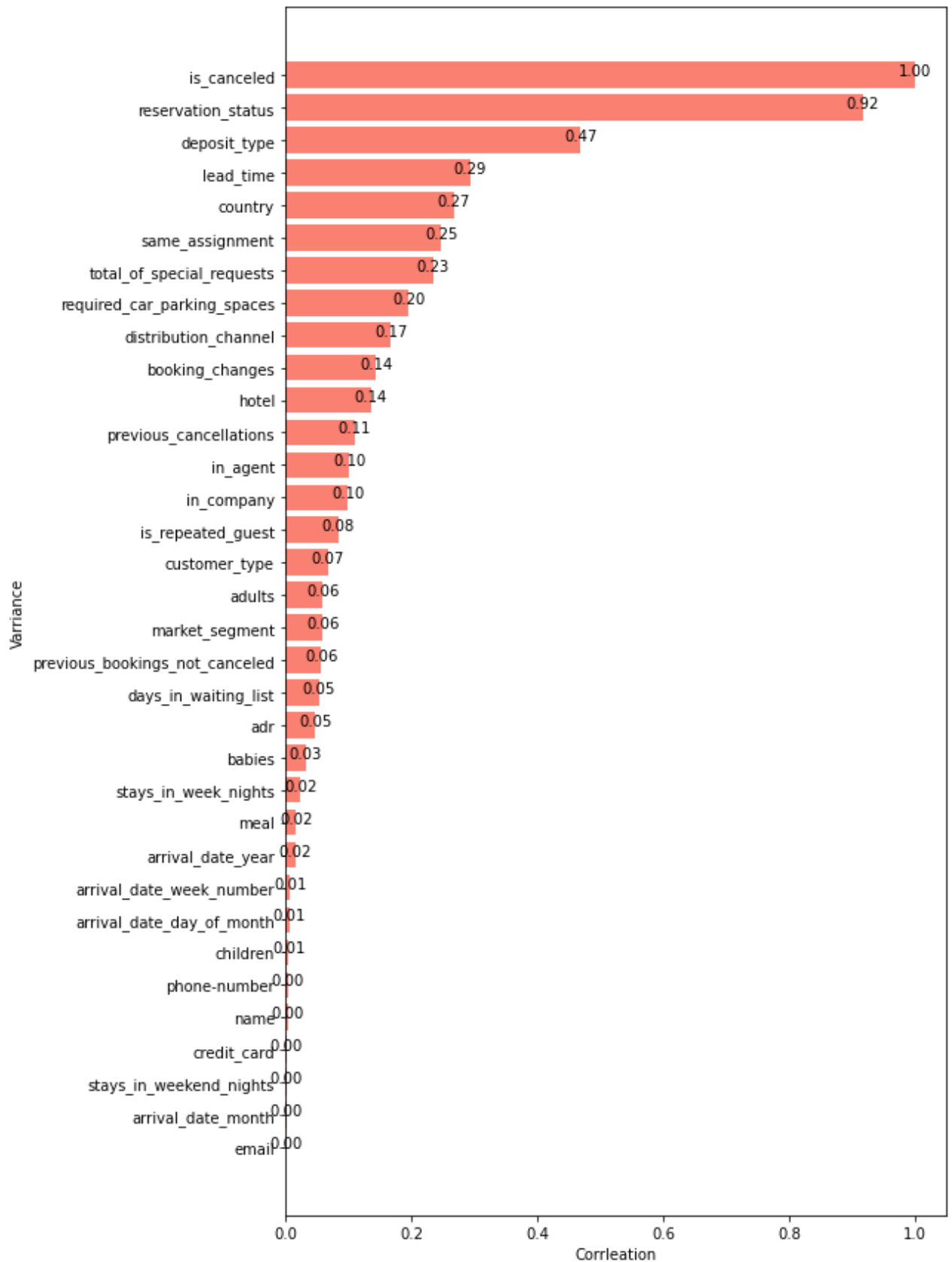
```

In [38]:

```

#create a horizontal bar plot using Matplotlib to visualize the absolute correlation va
plt.figure(figsize=(8,15))
x=range(len(cor.index))
name=cor.index
y=abs(cor.values)
plt.barh(x,y,color='salmon')
plt.yticks(x,name)
for x,y in zip(x,y):
    plt.text(y,x-0.1,'%.2f' % y,ha = 'center',va = 'bottom')
plt.xlabel('Corrleation')
plt.ylabel('Varriance')
plt.show()

```



The reservation status ('reservation_status') has the highest correlation with whether to cancel the reservation, reaching 0.92, but considering that it may cause the model to overfit in the future, it is deleted; the deposit type ('deposit_type') reaches 0.47, creating a characteristic Whether the reservation and assigned room type are consistent ('same_assignment') also has a correlation of 0.25.

In [39]: `#copy 'df1' with the column labeled 'reservation_status' dropped.
df2=df1.drop('reservation_status',axis=1)`

Week 5

In [40]: `df2.head()`

Out[40]:

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_week_number	arrival_
0	1.0	0	2.227051	-1.634768	5.0	-0.012141	
1	1.0	0	5.923385	-1.634768	5.0	-0.012141	
2	1.0	0	-0.907814	-1.634768	5.0	-0.012141	
3	1.0	0	-0.851667	-1.634768	5.0	-0.012141	
4	1.0	0	-0.842309	-1.634768	5.0	-0.012141	

5 rows × 33 columns



In [41]: `df2.var()`

Out[41]:

hotel	2.229544e-01
is_canceled	2.332100e-01
lead_time	1.000008e+00
arrival_date_year	1.000008e+00
arrival_date_month	1.249675e+01
arrival_date_week_number	1.000008e+00
arrival_date_day_of_month	1.000008e+00
stays_in_weekend_nights	1.000008e+00
stays_in_week_nights	1.000008e+00
adults	1.000008e+00
children	1.000008e+00
babies	1.000008e+00
meal	1.141902e+00
country	1.995000e+03
market_segment	1.604594e+00
distribution_channel	8.236978e-01
is_repeated_guest	3.089409e-02
previous_cancellations	1.000008e+00
previous_bookings_not_canceled	1.000008e+00
booking_changes	1.000008e+00
deposit_type	1.120096e-01
days_in_waiting_list	1.000008e+00
customer_type	3.329753e-01
adr	1.000008e+00
required_car_parking_spaces	1.000008e+00
total_of_special_requests	1.000008e+00
name	5.369325e+08
email	1.114750e+09
phone-number	1.187841e+09

```

credit_card      6.748231e+06
in_company       5.369037e-02
in_agent         1.181321e-01
same_assignment  1.093335e-01
dtype: float64

```

```

In [42]: #divide feature x and label y
x=df2.loc[:,df2.columns != 'is_canceled' ]
y=df2.loc[:, 'is_canceled']
from sklearn.model_selection import train_test_split as tts
xtrain,xtest,ytrain,ytest=tts(x,y,test_size=0.3,random_state=90)
for i in [xtrain,xtest,ytrain,ytest]:
    i.index=range(i.shape[0])

```

```

In [43]: x.shape, y.shape

```

```

Out[43]: ((119390, 32), (119390,))

```

```

In [44]: xtrain.head()

```

```

Out[44]:
   hotel  lead_time  arrival_date_year  arrival_date_month  arrival_date_week_number  arrival_date_day_of_i
0     0.0    1.029252         1.192195             5.0             0.061361             -0.5
1     0.0    0.102829        -0.221286             8.0            -0.600156             -1.5
2     1.0    0.168334         1.192195             6.0            -0.085642             1.6
3     1.0    0.767233         1.192195             5.0            -0.012141             -0.8
4     0.0   -0.421208        -0.221286            11.0             0.943385             1.1

```

5 rows × 32 columns



```

In [45]: xtest.head()

```

```

Out[45]:
   hotel  lead_time  arrival_date_year  arrival_date_month  arrival_date_week_number  arrival_date_day_of_i
0     0.0   -0.963961        -1.634768             2.0             1.898910             1.2
1     0.0   -0.861025        -0.221286             5.0             0.208365             0.3
2     0.0    1.431638        -0.221286             5.0             0.355369             1.7
3     0.0   -0.879741        -0.221286            11.0             0.722879             -1.2
4     0.0   -0.224694        -0.221286            11.0             0.943385             1.1

```

5 rows × 32 columns



```
In [46]: ytrain.head(), ytest.head()
```

```
Out[46]: (0    1
1     0
2     0
3     1
4     0
Name: is_canceled, dtype: int64,
0     0
1     0
2     0
3     0
4     0
Name: is_canceled, dtype: int64)
```

Week 6(XGBoost)

```
In [47]: from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, f1_score, roc_auc_score
from sklearn.model_selection import train_test_split

# Define the models with different hyperparameters
XGmodel_variations = {
    'XGmodel_1': XGBClassifier(n_estimators=100, learning_rate=0.1, random_state=90),
    'XGmodel_2': XGBClassifier(n_estimators=100, learning_rate=0.01, random_state=90),
    'XGmodel_3': XGBClassifier(n_estimators=100, learning_rate=0.1, max_depth=3, random
}

# Dictionary to store the performance metrics for each model
performance_metrics = {}
```

```
In [48]: # Train each model and calculate metrics
for name, model in XGmodel_variations.items():
    model.fit(xtrain, ytrain)
    ytrain_pred = model.predict(xtrain)
    ytest_pred = model.predict(xtest)

    performance_metrics[name] = {
        'train_accuracy': accuracy_score(ytrain, ytrain_pred),
        'train_f1': f1_score(ytrain, ytrain_pred),
        'train_roc_auc': roc_auc_score(ytrain, ytrain_pred),
        'test_accuracy': accuracy_score(ytest, ytest_pred),
        'test_f1': f1_score(ytest, ytest_pred),
        'test_roc_auc': roc_auc_score(ytest, ytest_pred)
    }
```

```
In [49]: # Output the performance metrics
for model, metrics in performance_metrics.items():
    print(f"Metrics for {model}:")
    for metric_name, metric_value in metrics.items():
        print(f"{metric_name}: {metric_value}")
```

```

Metrics for XGmodel_1:
train_accuracy: 0.8655307336101372
train_f1: 0.8111514418229482
train_roc_auc: 0.8473398907978615
test_accuracy: 0.8603456459223274
test_f1: 0.8015079365079366
test_roc_auc: 0.8411108612062882
Metrics for XGmodel_2:
train_accuracy: 0.8131094970863796
train_f1: 0.7025688877039971
train_roc_auc: 0.7683183623199193
test_accuracy: 0.8147248513275819
test_f1: 0.7020206555904804
test_roc_auc: 0.7685136787353957
Metrics for XGmodel_3:
train_accuracy: 0.8441123329304919
train_f1: 0.776189658134341
train_roc_auc: 0.8201658933607971
test_accuracy: 0.8434263059441047
test_f1: 0.7727346409466689
test_roc_auc: 0.8186964422810334

```

In [50]:

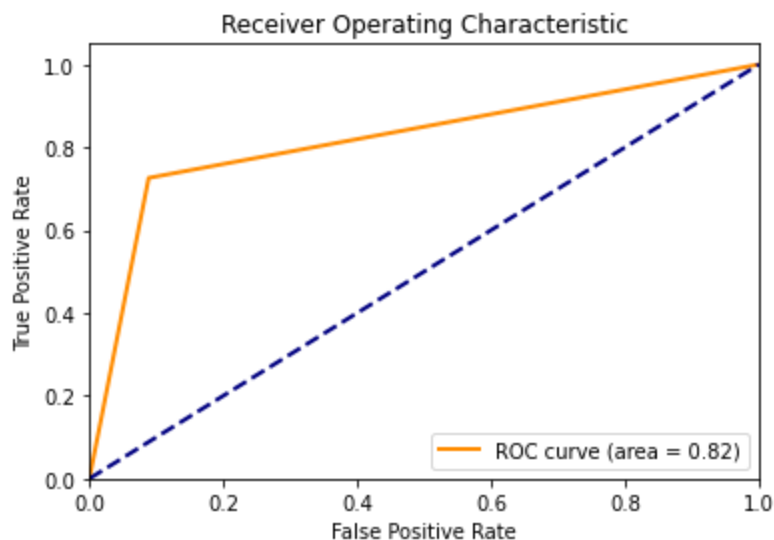
```

from sklearn.metrics import roc_curve, auc

# Compute ROC curve and ROC area for each class
fpr, tpr, _ = roc_curve(ytest, ytest_pred)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()

```



Week 7 (Logistic)

```
In [51]: from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.model_selection import train_test_split

# Define the models with different hyperparameters
LGmodel_variations = {
    'LGmodel_1': LogisticRegression(C=1.0, max_iter=100, solver='lbfgs', random_state=9),
    'LGmodel_2': LogisticRegression(C=0.5, max_iter=100, solver='lbfgs', random_state=9),
    'LGmodel_3': LogisticRegression(C=1.0, max_iter=200, solver='liblinear', random_state=9)
}

# Dictionary to store the performance metrics for each model
performance_metrics = {}
```

```
In [52]: # Train each model and calculate metrics
for name, model in LGmodel_variations.items():
    model.fit(xtrain, ytrain)
    ytrain_pred = model.predict(xtrain)
    ytest_pred = model.predict(xtest)

    performance_metrics[name] = {
        'train_accuracy': accuracy_score(ytrain, ytrain_pred),
        'train_precision': precision_score(ytrain, ytrain_pred),
        'train_recall': recall_score(ytrain, ytrain_pred),
        'train_f1': f1_score(ytrain, ytrain_pred),
        'test_accuracy': accuracy_score(ytest, ytest_pred),
        'test_precision': precision_score(ytest, ytest_pred),
        'test_recall': recall_score(ytest, ytest_pred),
        'test_f1': f1_score(ytest, ytest_pred)
    }
```

```
In [53]: # Output the performance metrics
for model, metrics in performance_metrics.items():
    print(f"Metrics for {model}:")
    for metric_name, metric_value in metrics.items():
        print(f"{metric_name}: {metric_value}")
```

```
Metrics for LGmodel_1:
train_accuracy: 0.6254292654326158
train_precision: 0.4935769857065316
train_recall: 0.2632273005049693
train_f1: 0.34334619902668234
test_accuracy: 0.6269648490940056
test_precision: 0.48432343234323433
test_recall: 0.2681793954161273
test_f1: 0.3452095074736584
Metrics for LGmodel_2:
train_accuracy: 0.6254292654326158
train_precision: 0.4935769857065316
train_recall: 0.2632273005049693
train_f1: 0.34334619902668234
test_accuracy: 0.6269648490940056
```



```

test_precision: 0.48432343234323433
test_recall: 0.2681793954161273
test_f1: 0.3452095074736584
Metrics for LGmodel_3:
train_accuracy: 0.6293061156115013
train_precision: 0.5035542747358309
train_recall: 0.25290276929014827
train_f1: 0.3367019226651822
test_accuracy: 0.6295334617639669
test_precision: 0.4900351699882767
test_recall: 0.25462575192263764
test_f1: 0.33512050909455326

```

In [54]:

```

# Initialize a plt.figure to plot
plt.figure(figsize=(10, 8))

# Iterate over each model to calculate ROC curve and AUC
for name, model in LGmodel_variations.items():
    # Fit the model
    model.fit(xtrain, ytrain)

    # Get the prediction probabilities for the positive class
    ytest_proba = model.predict_proba(xtest)[: , 1]

    # Calculate ROC curve and ROC area
    fpr, tpr, _ = roc_curve(ytest, ytest_proba)
    roc_auc = auc(fpr, tpr)

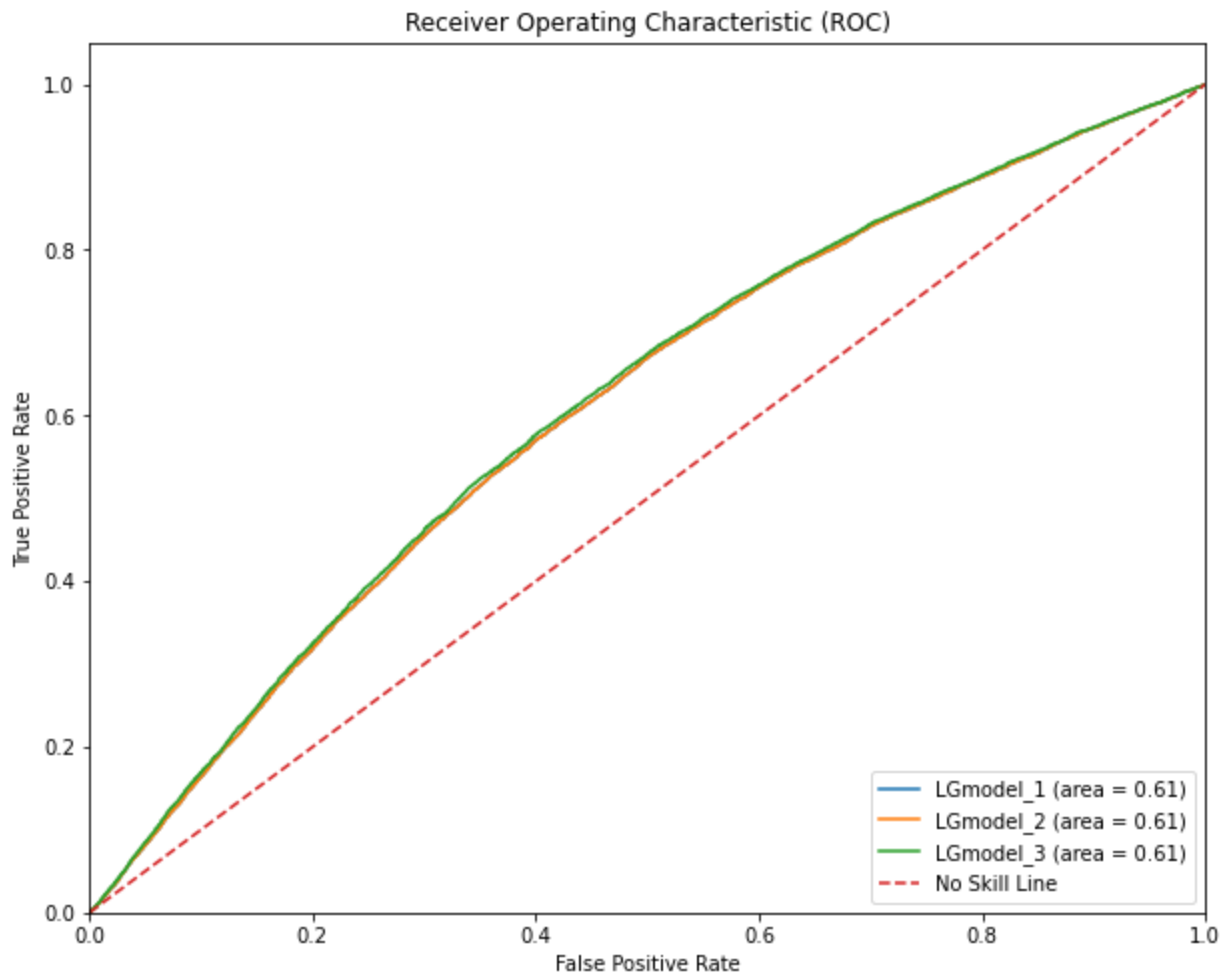
    # Plot ROC curve
    plt.plot(fpr, tpr, label=f'{name} (area = {roc_auc:.2f})')

# Plot the No Skill Line
plt.plot([0, 1], [0, 1], linestyle='--', label='No Skill Line')

# Formatting the plot
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")

```

Out[54]: <matplotlib.legend.Legend at 0x224c58cf130>



Week 8

```
In [55]: from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.model_selection import train_test_split

# Define the models with different hyperparameters
RFmodel_variations = {
    'RFmodel_1': RandomForestClassifier(n_estimators=100, max_depth=10, random_state=90),
    'RFmodel_2': RandomForestClassifier(n_estimators=200, max_depth=15, min_samples_split=10),
    'RFmodel_3': RandomForestClassifier(n_estimators=300, max_depth=20, min_samples_split=10)
}

# Dictionary to store the performance metrics for each model
performance_metrics = {}
```

```
In [56]: # Train each model and calculate metrics
for name, model in RFmodel_variations.items():
    model.fit(xtrain, ytrain)
    ytrain_pred = model.predict(xtrain)
    ytest_pred = model.predict(xtest)

    performance_metrics[name] = {
        'train_accuracy': accuracy_score(ytrain, ytrain_pred),
        'train_precision': precision_score(ytrain, ytrain_pred),
```

```

    'train_recall': recall_score(ytrain, ytrain_pred),
    'train_f1': f1_score(ytrain, ytrain_pred),
    'test_accuracy': accuracy_score(ytest, ytest_pred),
    'test_precision': precision_score(ytest, ytest_pred),
    'test_recall': recall_score(ytest, ytest_pred),
    'test_f1': f1_score(ytest, ytest_pred)
}

```

In [57]:

```

# Output the performance metrics
for model, metrics in performance_metrics.items():
    print(f"Metrics for {model}:")
    for metric_name, metric_value in metrics.items():
        print(f"{metric_name}: {metric_value}")

```

```

Metrics for RFmodel_1:
train_accuracy: 0.8485994280449427
train_precision: 0.8733597926453912
train_recall: 0.6936090830143772
train_f1: 0.773174623093057
test_accuracy: 0.8475305022754558
test_precision: 0.8677852348993289
test_recall: 0.6891799284245793
test_f1: 0.7682383397699785
Metrics for RFmodel_2:
train_accuracy: 0.8822107618489226
train_precision: 0.8883851862684167
train_recall: 0.7815766620565437
train_f1: 0.8315652590513998
test_accuracy: 0.8634168132451071
test_precision: 0.8633918334950172
test_recall: 0.7454503921419325
test_f1: 0.8000980712651193
Metrics for RFmodel_3:
train_accuracy: 0.9223074437916552
train_precision: 0.9242204746136865
train_recall: 0.8618249654240777
train_f1: 0.8919328262570112
test_accuracy: 0.8700058631376162
test_precision: 0.8651046601774486
test_recall: 0.7647148404781847
test_f1: 0.8118179613612482

```

In [58]:

```

# Initialize a plt.figure to plot
plt.figure(figsize=(10, 8))

# Iterate over each model to calculate ROC curve and AUC
for name, model in RFmodel_variations.items():
    # Fit the model
    model.fit(xtrain, ytrain)

    # Get the prediction probabilities for the positive class
    ytest_proba = model.predict_proba(xtest)[: , 1]

    # Calculate ROC curve and ROC area
    fpr, tpr, _ = roc_curve(ytest, ytest_proba)
    roc_auc = auc(fpr, tpr)

    # Plot ROC curve

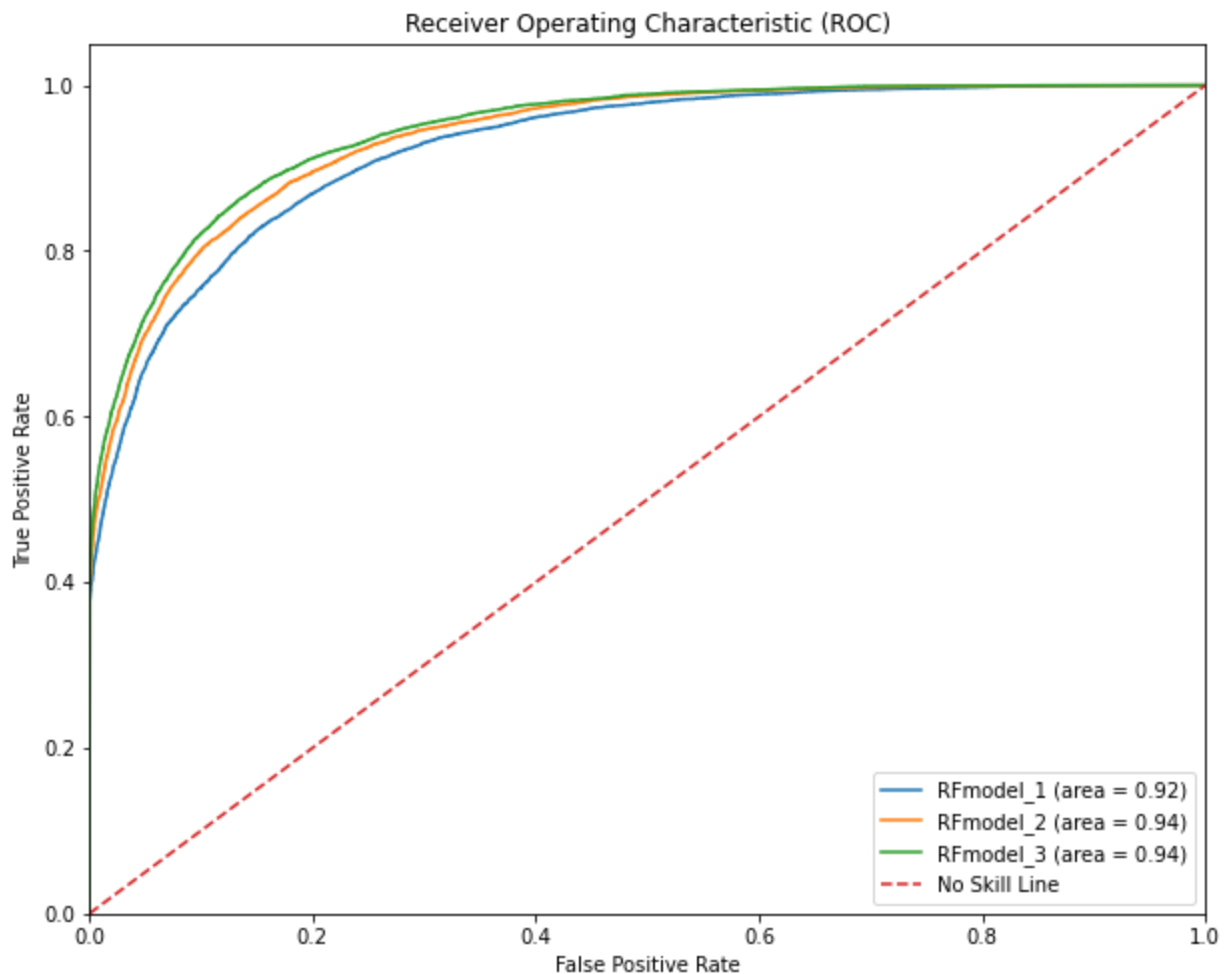
```

```
plt.plot(fpr, tpr, label=f'{name} (area = {roc_auc:.2f})')

# Plot the No Skill Line
plt.plot([0, 1], [0, 1], linestyle='--', label='No Skill Line')

# Formatting the plot
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")

# Show the plot
plt.show()
```



ANN

In [59]:

```
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, roc_auc_score

# df2 is my dataframe after preprocessing and 'is_canceled' is the target variable
x = df2.drop('is_canceled', axis=1).values # Converting to NumPy array for Keras
y = df2['is_canceled'].values

# Split the data into training and testing sets
```

```
xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.3, random_state=90)

# Define the hyperparameter settings for three variations
# Variation might include number of layers, number of neurons, activation functions, etc
# vary the number of neurons in the first layer
hyperparameter_variations = [
    {'first_layer_neurons': 16},
    {'first_layer_neurons': 32},
    {'first_layer_neurons': 64}
]

# Define a function to create a model
def create_model(first_layer_neurons):
    model = tf.keras.Sequential([
        tf.keras.layers.Dense(first_layer_neurons, activation='relu', input_shape=(xtrain.shape[1],)),
        tf.keras.layers.Dense(1, activation='sigmoid') # Output Layer
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
```

In [60]:

```
# Train and evaluate each model variation
for i, params in enumerate(hyperparameter_variations, start=1):
    model = create_model(**params)
    model.fit(xtrain, ytrain, epochs=10, batch_size=32, verbose=0) # You can adjust epochs

    # Predict on training and validation set
    ytrain_pred = (model.predict(xtrain) > 0.5).astype("int32")
    ytest_pred = (model.predict(xtest) > 0.5).astype("int32")

    # Calculate performance metrics for both training and test datasets
    metrics = {
        'train_accuracy': accuracy_score(ytrain, ytrain_pred),
        'train_f1': f1_score(ytrain, ytrain_pred),
        'train_roc_auc': roc_auc_score(ytrain, ytrain_pred.ravel()),
        'test_accuracy': accuracy_score(ytest, ytest_pred),
        'test_f1': f1_score(ytest, ytest_pred),
        'test_roc_auc': roc_auc_score(ytest, ytest_pred.ravel())
    }

    # Print the performance metrics
    print(f"Model Variation {i}: {params}")
    print("Training Metrics:", metrics['train_accuracy'], metrics['train_f1'], metrics['train_roc_auc'])
    print("Test Metrics:", metrics['test_accuracy'], metrics['test_f1'], metrics['test_roc_auc'])
    print("-" * 30)
```

```
2612/2612 [=====] - 2s 803us/step
1120/1120 [=====] - 1s 832us/step
Model Variation 1: {'first_layer_neurons': 16}
Training Metrics: 0.6591602551063143 0.17451531573303966 0.544563907274308
Test Metrics: 0.6631208643940029 0.16889378702300592 0.543171638684316
-----
2612/2612 [=====] - 2s 790us/step
1120/1120 [=====] - 1s 817us/step
Model Variation 2: {'first_layer_neurons': 32}
Training Metrics: 0.6827085302669522 0.5533377128707868 0.6512385874096658
Test Metrics: 0.6841723204065109 0.5497173791895551 0.650826018089848
-----
2612/2612 [=====] - 2s 724us/step
1120/1120 [=====] - 1s 870us/step
```

Model Variation 3: {'first_layer_neurons': 64}
 Training Metrics: 0.6560252713196846 0.4221824686940966 0.591169433432359
 Test Metrics: 0.6576765223218025 0.4187722209054278 0.5900253903732715

Week 9

```
In [61]: # Split the training set into a smaller training set and a validation set
xtrain_new, xval, ytrain_new, yval = train_test_split(xtrain, ytrain, test_size=0.2, ra
```

```
In [62]: from sklearn.metrics import roc_auc_score
# Evaluate all models using the validation dataset
validation_scores = {}
for name, model in (**XGmodel_variations, **LGmodel_variations, **RFmodel_variations).i
    yval_pred = model.predict_proba(xval)[: , 1]
    validation_scores[name] = roc_auc_score(yval, yval_pred)
```

```
In [63]: # Select the winning model
winning_model_name = max(validation_scores, key=validation_scores.get)
winning_model = (**XGmodel_variations, **LGmodel_variations, **RFmodel_variations)[winn

# Output the performance of the winning model on the test dataset
ytest_pred = winning_model.predict_proba(xtest)[: , 1]
test_auc = roc_auc_score(ytest, ytest_pred)

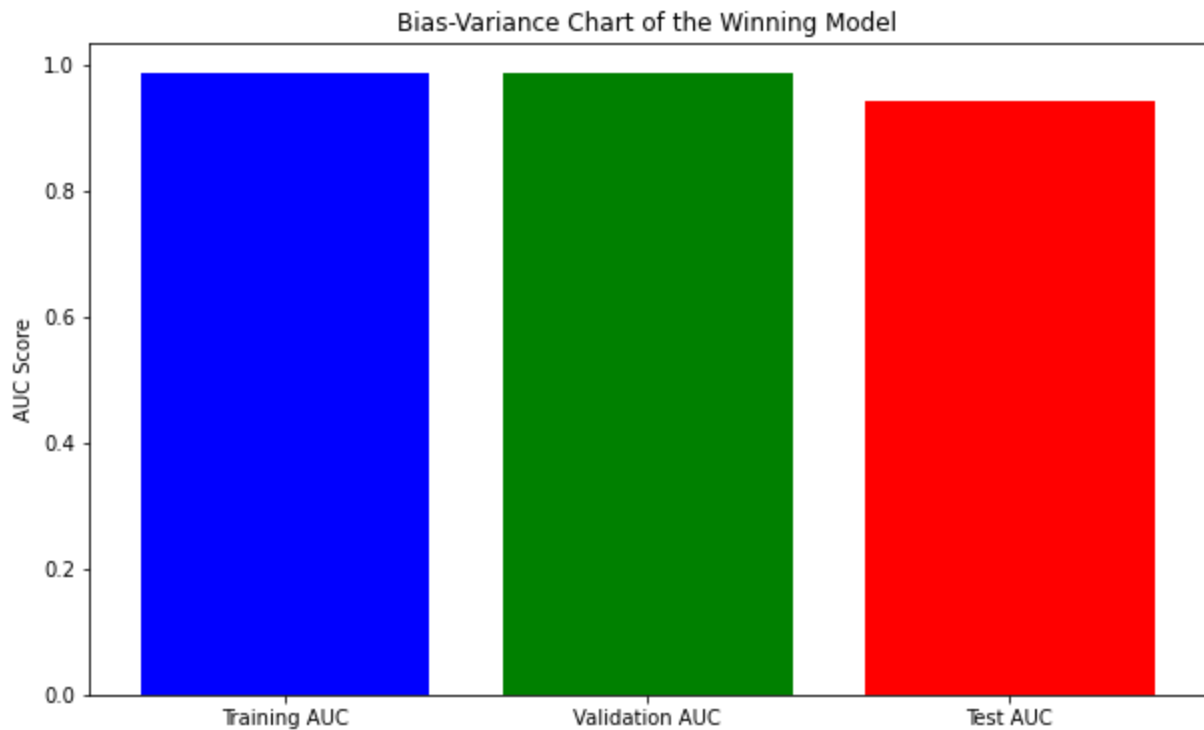
print(f"Winning model: {winning_model_name} with validation AUC: {validation_scores[winn
print(f"Winning model performance on the test dataset: AUC: {test_auc}")
```

Winning model: RFmodel_3 with validation AUC: 0.9862408203027578
 Winning model performance on the test dataset: AUC: 0.9440211958436756

```
In [64]: # Bias-Variance Trade-off Analysis
# For a full bias-variance analysis, Look at the model's performance across multiple tr
# compare training score vs. validation score as a proxy.
train_auc = roc_auc_score(ytrain, winning_model.predict_proba(xtrain)[: , 1])
print(f"Winning model performance on the training dataset: AUC: {train_auc}")
```

Winning model performance on the training dataset: AUC: 0.9863891690363809

```
In [65]: # Plotting the Bias-Variance chart
# plotting only AUC scores
plt.figure(figsize=(10, 6))
plt.bar(['Training AUC', 'Validation AUC', 'Test AUC'], [train_auc, validation_scores[w
plt.ylabel('AUC Score')
plt.title('Bias-Variance Chart of the Winning Model')
plt.show()
```



Week 10

```
In [66]: # Handling missing values for numerical features with median
for column in df2.select_dtypes(include=['float64', 'int64']).columns:
    df2[column].fillna(df2[column].median(), inplace=True)

# Creating new features that might help improve model performance
df2['total_stays'] = df2['stays_in_weekend_nights'] + df2['stays_in_week_nights']

# Split the data into features and target again after the enhancements
x = df2.loc[:, df2.columns != 'is_canceled']
y = df2.loc[:, 'is_canceled']

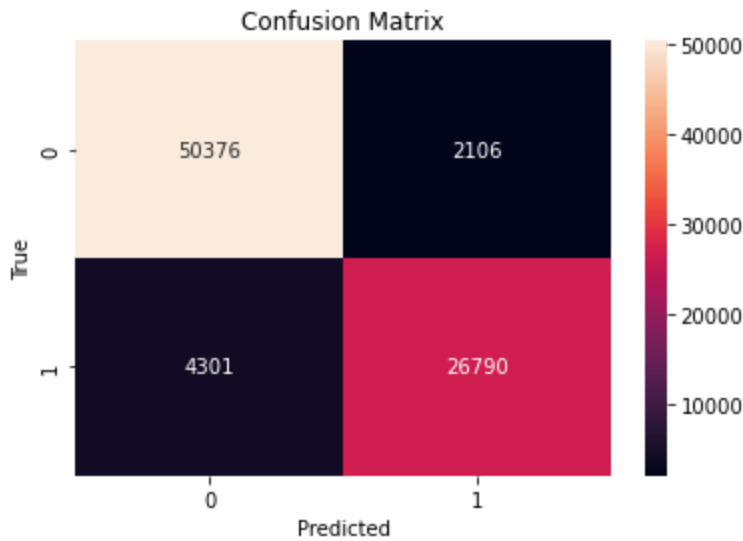
# Re-split the data into training, validation, and test sets
x_train, x_val_test, y_train, y_val_test = train_test_split(x, y, test_size=0.3, random
x_val, x_test, y_val, y_test = train_test_split(x_val_test, y_val_test, test_size=0.5,
```

```
In [67]: # Use RFmodel_3, the winning model as my model
model = RandomForestClassifier(n_estimators=300, max_depth=20, min_samples_split=6, ran
model.fit(x_train, y_train)
y_train_pred = model.predict(x_train)

# Analyze where the model is making errors
errors = y_train != y_train_pred
error_indices = errors[errors].index
error_data = x_train.loc[error_indices]
```

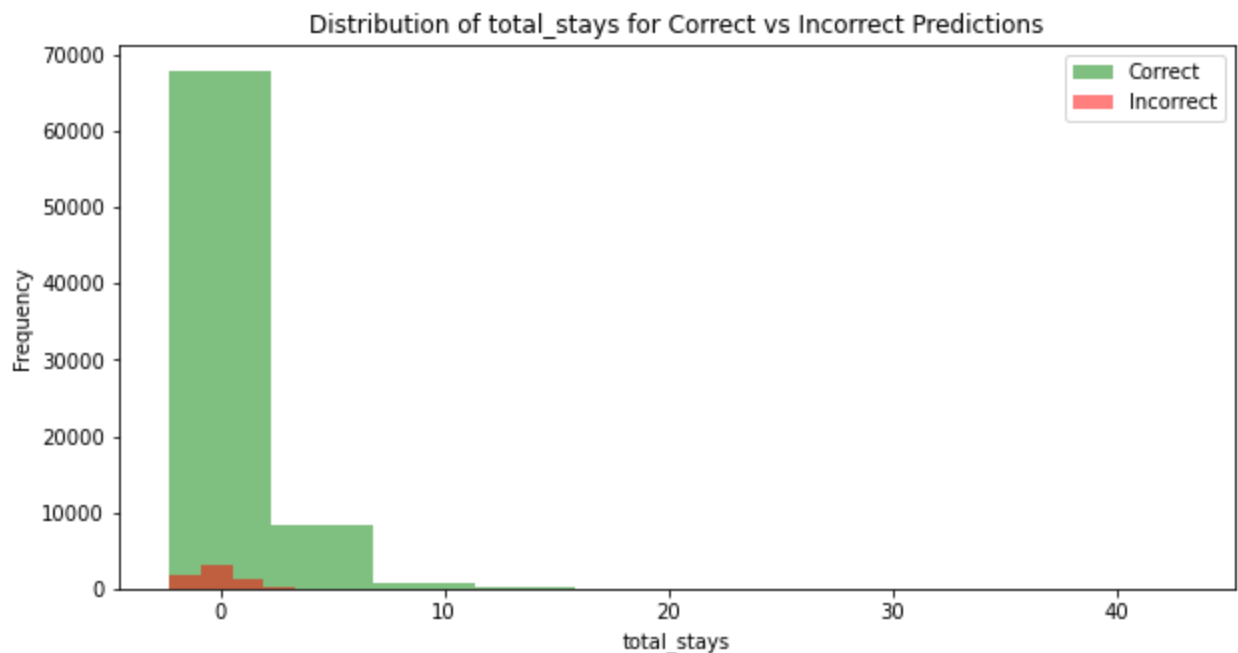
```
In [68]: from sklearn.metrics import confusion_matrix
import seaborn as sns
cm = confusion_matrix(y_train, y_train_pred)
sns.heatmap(cm, annot=True, fmt='d')
```

```
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



In [69]:

```
feature = 'total_stays'
# Plot the distribution of the feature for correct and incorrect predictions
plt.figure(figsize=(10, 5))
plt.hist(x_train.loc[~errors, feature], color='green', alpha=0.5, label='Correct')
plt.hist(x_train.loc[errors, feature], color='red', alpha=0.5, label='Incorrect')
plt.xlabel(feature)
plt.ylabel('Frequency')
plt.title(f'Distribution of {feature} for Correct vs Incorrect Predictions')
plt.legend()
plt.show()
```

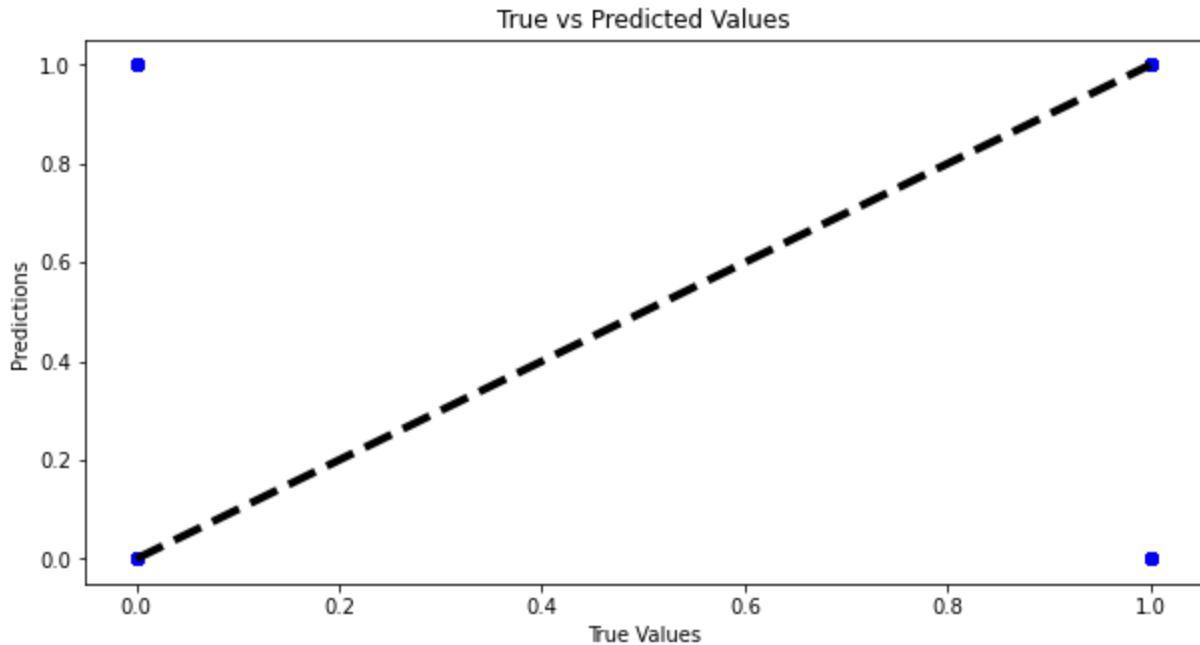


In [70]:

```
plt.figure(figsize=(10, 5))
plt.scatter(y_train, y_train_pred, color='blue')
plt.plot([y_train.min(), y_train.max()], [y_train.min(), y_train.max()], 'k--', lw=4)
```

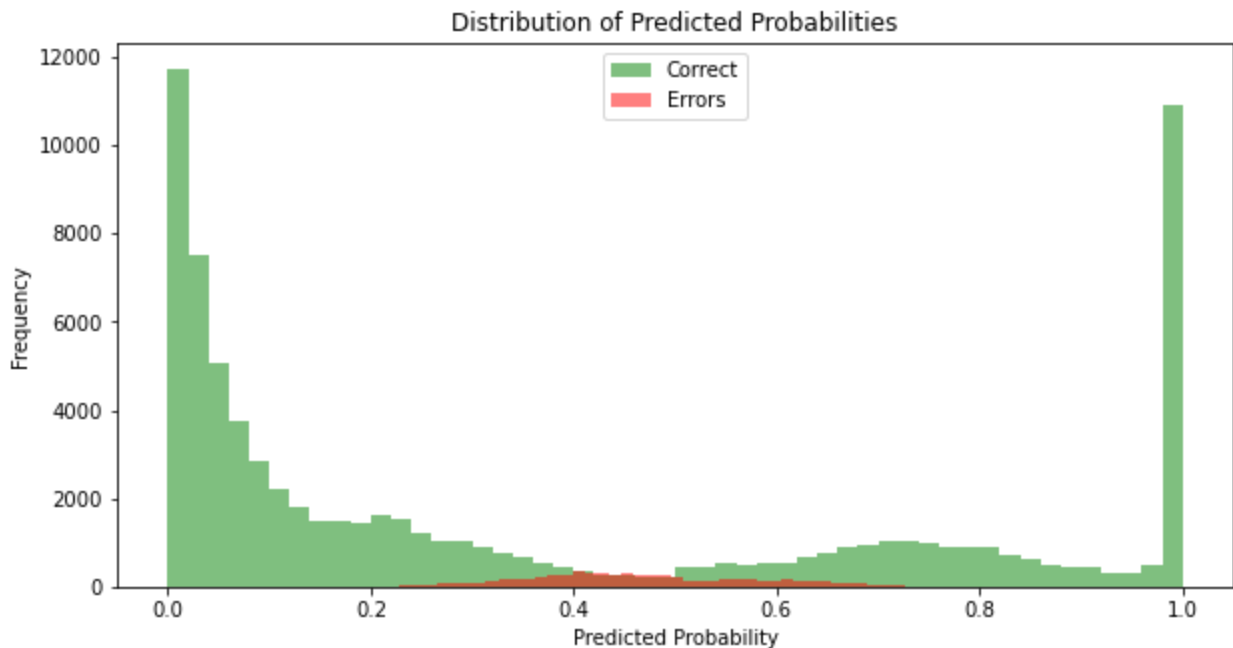


```
plt.xlabel('True Values')
plt.ylabel('Predictions')
plt.title('True vs Predicted Values')
plt.show()
```



In [71]:

```
# For binary classification
probabilities = model.predict_proba(x_train)[: , 1]
plt.figure(figsize=(10, 5))
plt.hist(probabilities[~errors], bins=50, color='green', alpha=0.5, label='Correct')
plt.hist(probabilities[errors], bins=50, color='red', alpha=0.5, label='Errors')
plt.xlabel('Predicted Probability')
plt.ylabel('Frequency')
plt.title('Distribution of Predicted Probabilities')
plt.legend()
plt.show()
```



```
In [72]: # Refit the model to the new training dataset
model.fit(x_train, y_train)
```

```
Out[72]: ▼ Random Forest Classifier
RandomForestClassifier(max_depth=20, min_samples_split=6, n_estimators=300,
random_state=90)
```

```
In [73]: # Evaluate the model's performance on the new training dataset
y_train_pred = model.predict(x_train)
train_accuracy = accuracy_score(y_train, y_train_pred)

# Evaluate the model's performance on the new validation dataset
y_val_pred = model.predict(x_val)
val_accuracy = accuracy_score(y_val, y_val_pred)

# Evaluate the model's performance on the new test dataset
y_test_pred = model.predict(x_test)
test_accuracy = accuracy_score(y_test, y_test_pred)

# Output the performance
print(f"Training Accuracy: {train_accuracy}")
print(f"Validation Accuracy: {val_accuracy}")
print(f"Test Accuracy: {test_accuracy}")
```

Training Accuracy: 0.9233364842712359
Validation Accuracy: 0.8701139155684611
Test Accuracy: 0.8705120330560053

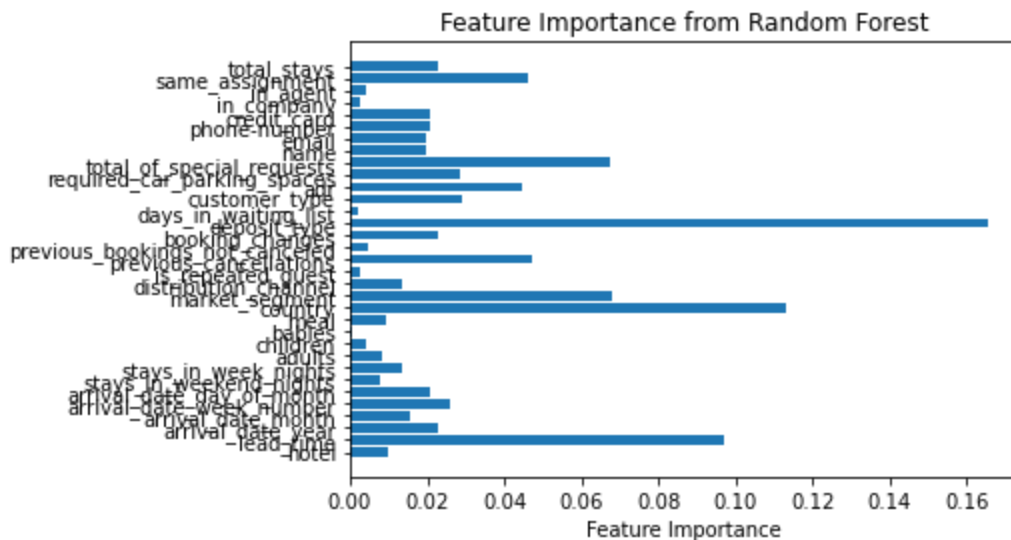
Week 11

```
In [74]: from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(n_estimators=300, max_depth=20, min_samples_split=6, random_state=90)
model.fit(x_train, y_train)

# Get feature importances
importances = model.feature_importances_

# Plot feature importances
plt.barh(range(len(importances)), importances, align='center')
plt.yticks(range(len(importances)), x_train.columns)
plt.xlabel('Feature Importance')
plt.title('Feature Importance from Random Forest')
plt.show()
```



In [75]:

!pip install lime

```
Requirement already satisfied: lime in c:\users\zhumh\anaconda3\lib\site-packages (0.2.0.1)
Requirement already satisfied: scipy in c:\users\zhumh\anaconda3\lib\site-packages (from lime) (1.7.1)
Requirement already satisfied: matplotlib in c:\users\zhumh\anaconda3\lib\site-packages (from lime) (3.4.3)
Requirement already satisfied: tqdm in c:\users\zhumh\anaconda3\lib\site-packages (from lime) (4.66.1)
Requirement already satisfied: numpy in c:\users\zhumh\anaconda3\lib\site-packages (from lime) (1.22.4)
Requirement already satisfied: scikit-learn>=0.18 in c:\users\zhumh\anaconda3\lib\site-packages (from lime) (1.2.2)
Requirement already satisfied: scikit-image>=0.12 in c:\users\zhumh\anaconda3\lib\site-packages (from lime) (0.18.3)
Requirement already satisfied: networkx>=2.0 in c:\users\zhumh\anaconda3\lib\site-packages (from scikit-image>=0.12->lime) (2.6.3)
Requirement already satisfied: pillow!=7.1.0,!>=7.1.1,>=4.3.0 in c:\users\zhumh\anaconda3\lib\site-packages (from scikit-image>=0.12->lime) (8.4.0)
Requirement already satisfied: imageio>=2.3.0 in c:\users\zhumh\anaconda3\lib\site-packages (from scikit-image>=0.12->lime) (2.9.0)
Requirement already satisfied: tifffile>=2019.7.26 in c:\users\zhumh\anaconda3\lib\site-packages (from scikit-image>=0.12->lime) (2021.7.2)
Requirement already satisfied: PyWavelets>=1.1.1 in c:\users\zhumh\anaconda3\lib\site-packages (from scikit-image>=0.12->lime) (1.1.1)
Requirement already satisfied: pyparsing>=2.2.1 in c:\users\zhumh\anaconda3\lib\site-packages (from matplotlib->lime) (3.0.4)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\zhumh\anaconda3\lib\site-packages (from matplotlib->lime) (1.3.1)
Requirement already satisfied: cycycler>=0.10 in c:\users\zhumh\anaconda3\lib\site-packages (from matplotlib->lime) (0.10.0)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\zhumh\anaconda3\lib\site-packages (from matplotlib->lime) (2.8.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\zhumh\anaconda3\lib\site-packages (from scikit-learn>=0.18->lime) (2.2.0)
Requirement already satisfied: joblib>=1.1.1 in c:\users\zhumh\anaconda3\lib\site-packages (from scikit-learn>=0.18->lime) (1.2.0)
Requirement already satisfied: colorama in c:\users\zhumh\anaconda3\lib\site-packages (from tqdm->lime) (0.4.4)
```

Requirement already satisfied: six in c:\users\zhumh\anaconda3\lib\site-packages (from cyclo>=0.10->matplotlib->lime) (1.16.0)

[notice] A new release of pip is available: 23.0 -> 23.3.1

[notice] To update, run: python.exe -m pip install --upgrade pip

In [76]:

```
from lime import lime_tabular

explainer = lime_tabular.LimeTabularExplainer(
    training_data=np.array(x_train),
    feature_names=x_train.columns,
    class_names=['Not Canceled', 'Canceled'],
    mode='classification'
)

# Select 5 random instances from the test set
np.random.seed(90)
random_indices = np.random.choice(x_test.index, size=5, replace=False)

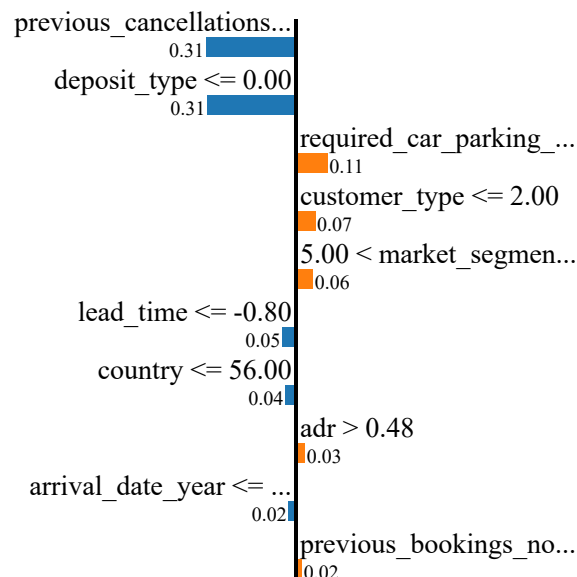
# Explain each of the 5 instances
for i in random_indices:
    exp = explainer.explain_instance(x_test.loc[i], model.predict_proba, num_features=1)
    exp.show_in_notebook(show_table=True, show_all=False)
```

Prediction probabilities



Not Canceled

Canceled



Feature Value

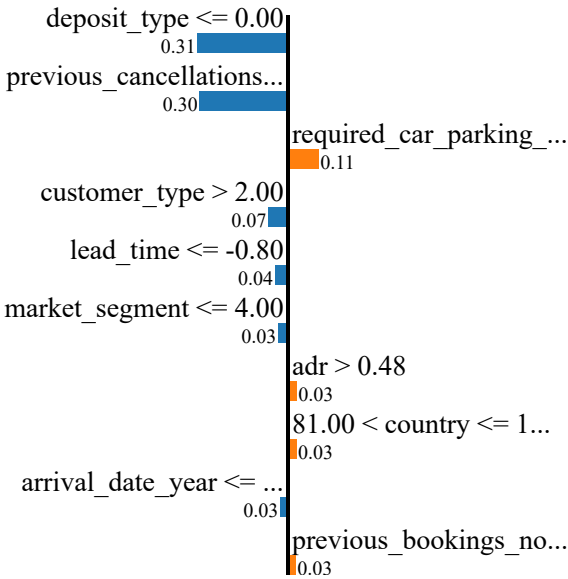
previous_cancellations	-0.10
deposit_type	0.00
required_car_parking_spaces	-0.25
customer_type	2.00
market_segment	6.00
lead_time	-0.92
country	1.00
adr	1.05

Prediction probabilities



Not Canceled

Canceled



Feature Value

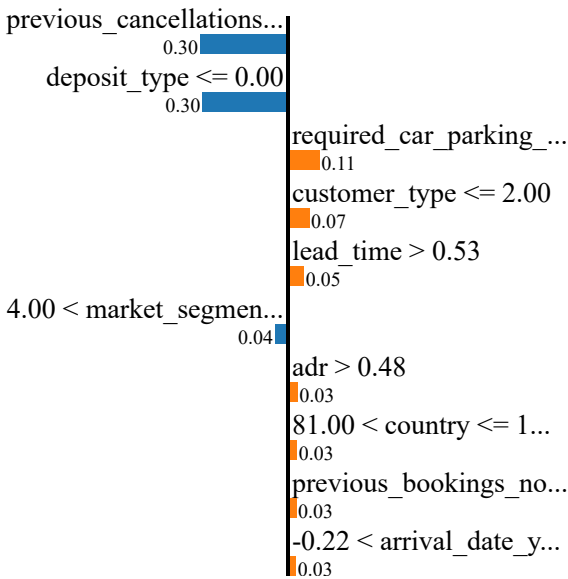
deposit_type	0.00
previous_cancellations	-0.10
required_car_parking_spaces	-0.25
customer_type	3.00
lead_time	-0.95
market_segment	2.00
adr	0.74
country	135.00
arrival date year	-0.22

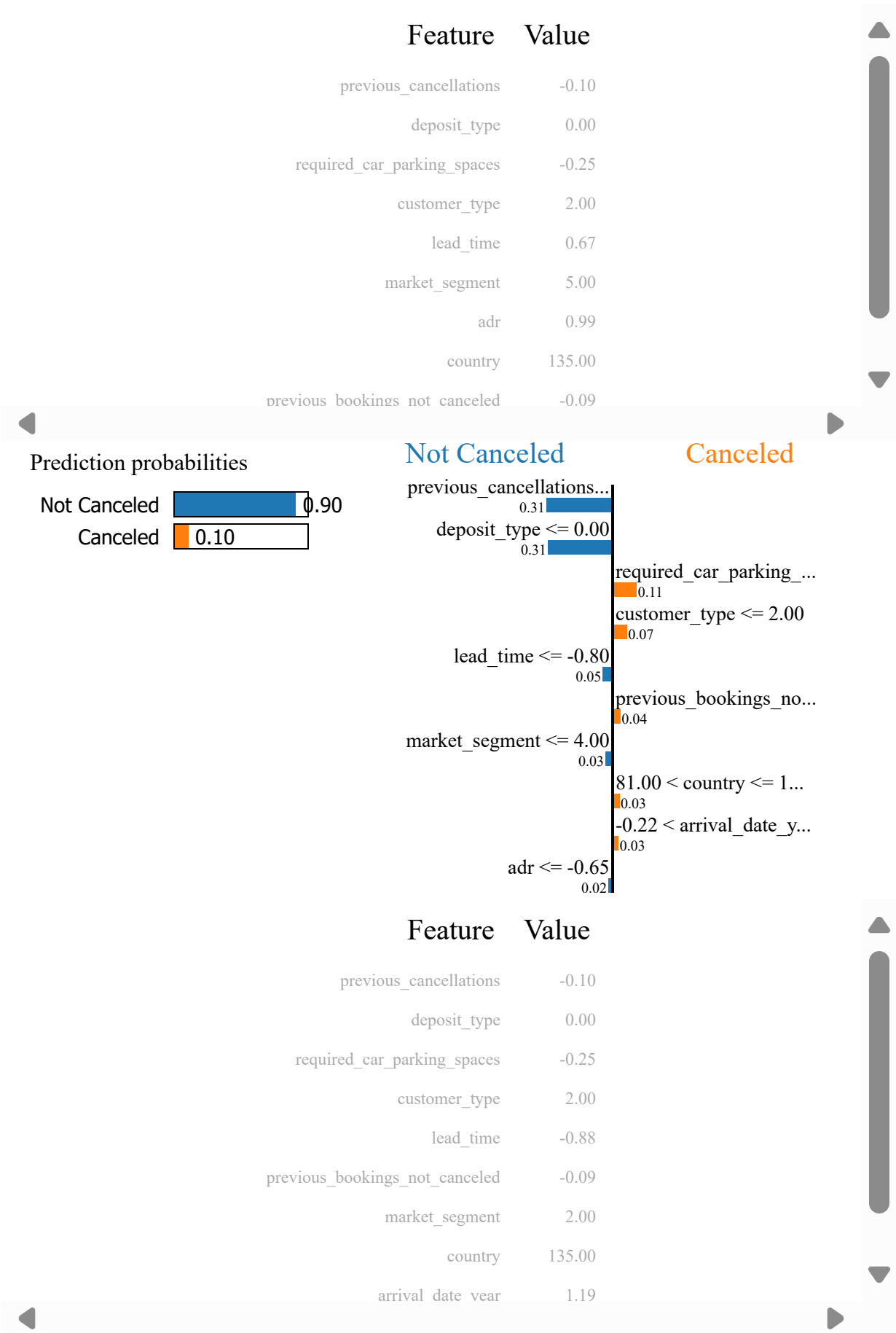
Prediction probabilities



Not Canceled

Canceled





Feature

Value

previous_cancellations

-0.10

deposit_type

0.00

required_car_parking_spaces

-0.25

customer_type

2.00

lead_time

-0.88

previous_bookings_not_canceled

-0.09

market_segment

2.00

country

135.00

arrival_date_year

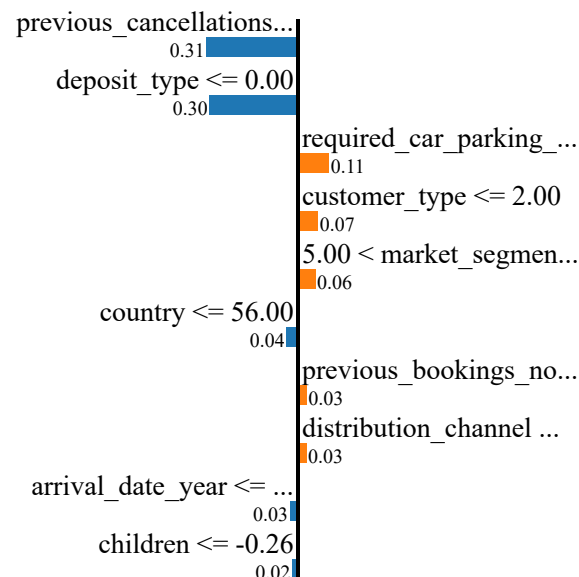
1.19

Prediction probabilities



Not Canceled

Canceled



Feature	Value
previous_cancellations	-0.10
deposit_type	0.00
required_car_parking_spaces	-0.25
customer_type	2.00
market_segment	6.00
country	43.00
previous_bookings_not_canceled	-0.09
distribution_channel	3.00
arrival date year	-0.22

In [77]:

```
# define the subgroups based on the country column. It's a list of countries from the b
countries = ['PRT', 'GBR', 'ESP', 'IRL', 'FRA', 'DEU', 'BEL', 'ITA', 'NLD', 'BRA']

# Create a dictionary to hold the data for each subgroup
subgroups = {country: df[df['country'] == country] for country in countries}

# perform analyses on each subgroup, such as calculating the cancellation rate
cancellation_rates = {}

for country, subgroup in subgroups.items():
    cancellation_rate = subgroup['is_canceled'].mean()
    cancellation_rates[country] = cancellation_rate

# Output the cancellation rates for each country
print("Cancellation rates by country:")
for country, rate in cancellation_rates.items():
    print(f"{country}: {rate:.2f}")
```

Cancellation rates by country:
PRT: 0.57

GBR: 0.20
 ESP: 0.25
 IRL: 0.25
 FRA: 0.19
 DEU: 0.17
 BEL: 0.20
 ITA: 0.35
 NLD: 0.18
 BRA: 0.37

In [78]:

```
median_stay = df2['total_stays'].median()

subgroups = {
    'Short Stays': df2[df2['total_stays'] <= median_stay],
    'Long Stays': df2[df2['total_stays'] > median_stay]
}
```

In [79]:

```
from sklearn.metrics import accuracy_score

# Calculate accuracy for each subgroup
bias_analysis = {}
for subgroup_name, subgroup_data in subgroups.items():
    x_subgroup = subgroup_data.drop(['is_canceled'], axis=1)
    y_subgroup = subgroup_data['is_canceled']
    y_pred_subgroup = model.predict(x_subgroup)
    accuracy_subgroup = accuracy_score(y_subgroup, y_pred_subgroup)
    bias_analysis[subgroup_name] = accuracy_subgroup

# Print the bias analysis results
for subgroup_name, accuracy in bias_analysis.items():
    print(f"{subgroup_name} Accuracy: {accuracy}")
```

Short Stays Accuracy: 0.9178891404942404

Long Stays Accuracy: 0.8965234054202026

In [80]:

```
# Strategies might include resampling, reweighting, or feature engineering, reweight the
from sklearn.utils import class_weight

class_weights = class_weight.compute_class_weight(
    'balanced',
    classes=np.unique(y_train),
    y=y_train
)

model.set_params(class_weight=dict(enumerate(class_weights)))
model.fit(x_train, y_train)
```

Out[80]:

```
RandomForestClassifier
RandomForestClassifier(class_weight={0: 0.7962063183567699,
                                     1: 1.3440063040751342},
                       max_depth=20, min_samples_split=6, n_estimators=300,
                       random_state=90)
```


In [81]:

```
# Evaluate the model on the training set
y_train_pred = model.predict(x_train)
train_accuracy_new = accuracy_score(y_train, y_train_pred)

# Evaluate the model on the validation set
y_val_pred = model.predict(x_val)
val_accuracy_new = accuracy_score(y_val, y_val_pred)

# Evaluate the model on the test set
y_test_pred = model.predict(x_test)
test_accuracy_new = accuracy_score(y_test, y_test_pred)

# Print the new performance metrics
print(f"New Training Accuracy: {train_accuracy_new}")
print(f"New Validation Accuracy: {val_accuracy_new}")
print(f"New Test Accuracy: {test_accuracy_new}")
```

New Training Accuracy: 0.9348473789381738
 New Validation Accuracy: 0.8730176457449185
 New Test Accuracy: 0.8672176000893406

In [82]:

```
# Compare the old and new performance metrics
print(f"Old Training Accuracy: {train_accuracy}") # actual value from Week 10
print(f"Old Validation Accuracy: {val_accuracy}") # actual value from Week 10
print(f"Old Test Accuracy: {test_accuracy}") # actual value from Week 10

print(f"New Training Accuracy: {train_accuracy_new}")
print(f"New Validation Accuracy: {val_accuracy_new}")
print(f"New Test Accuracy: {test_accuracy_new}")
```

Old Training Accuracy: 0.9233364842712359
 Old Validation Accuracy: 0.8701139155684611
 Old Test Accuracy: 0.8705120330560053
 New Training Accuracy: 0.9348473789381738
 New Validation Accuracy: 0.8730176457449185
 New Test Accuracy: 0.8672176000893406

In [83]:

```
# Data to plot
labels = ['Training Accuracy', 'Validation Accuracy', 'Test Accuracy']
old_acc = [train_accuracy, val_accuracy, test_accuracy]
new_acc = [train_accuracy_new, val_accuracy_new, test_accuracy_new]

# Convert range to list for arithmetic operations
x = list(range(len(labels)))
width = 0.35

fig, ax = plt.subplots(figsize=(10, 8)) # Increase the figure size
rects1 = ax.bar([p - width/2 for p in x], old_acc, width, label='Week 10')
rects2 = ax.bar([p + width/2 for p in x], new_acc, width, label='Post-Mitigation')

# Add labels, title, and custom x-axis tick labels
ax.set_ylabel('Accuracy')
ax.set_title('Accuracy by dataset and model iteration')
ax.set_xticks(x)
ax.set_xticklabels(labels, rotation=45)
ax.legend()
```

```

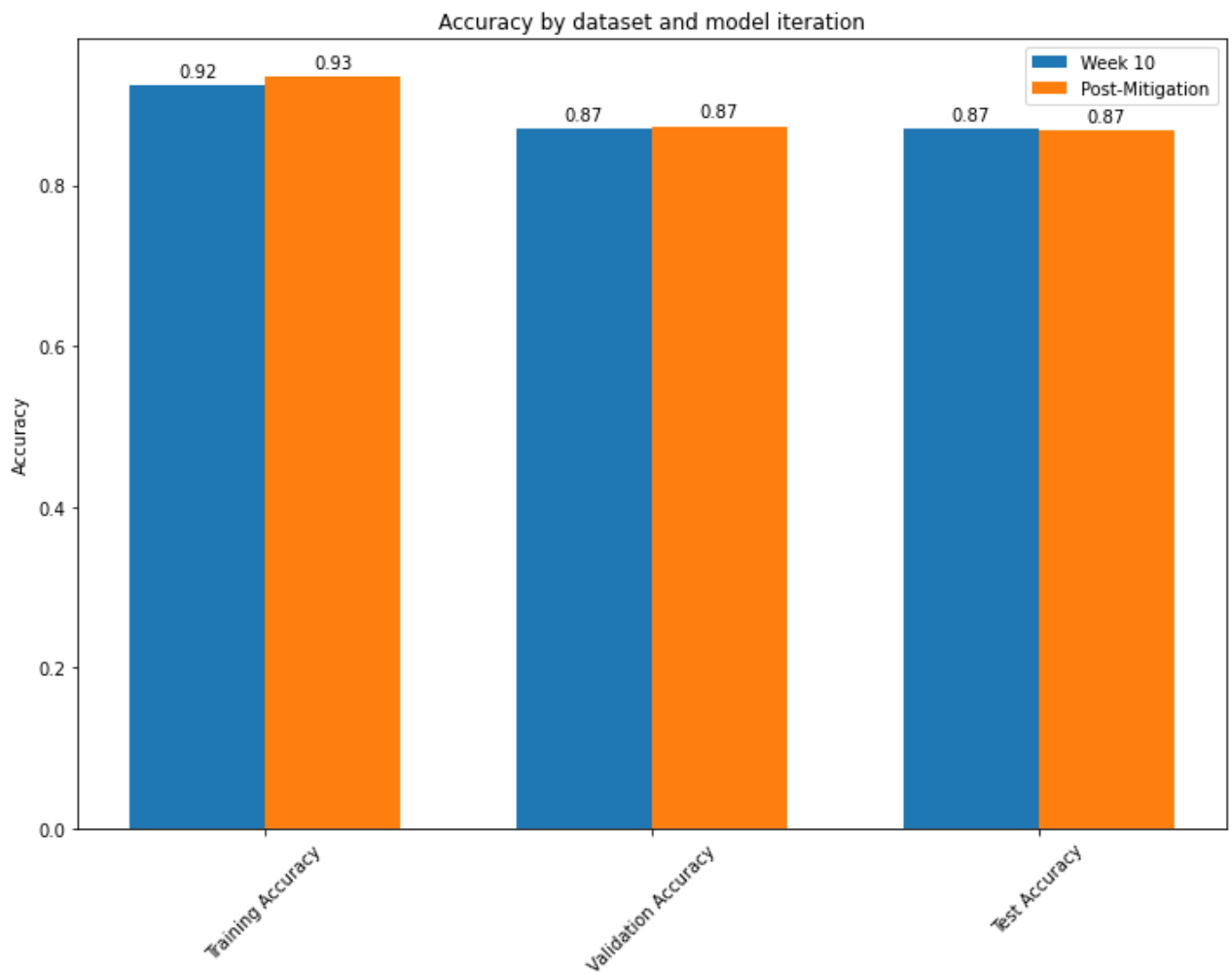
# Function to attach a text label above each bar
def autolabel(rects):
    for rect in rects:
        height = rect.get_height()
        ax.annotate(f'{height:.2f}', # Format the label to show only 2 decimal places
                    xy=(rect.get_x() + rect.get_width() / 2, height),
                    xytext=(0, 3),
                    textcoords="offset points",
                    ha='center', va='bottom')

autolabel(rects1)
autolabel(rects2)

fig.tight_layout()

plt.show()

```



Week 12

In [85]:

```

import pickle
from sklearn.ensemble import RandomForestClassifier

# I have a trained model named 'model'
model = RandomForestClassifier()
model.fit(x_train, y_train)

```

```
# Serialize the model to a file
with open('model.pkl', 'wb') as file:
    pickle.dump(model, file)
```

```
In [86]: # Load the model from the file
with open('model.pkl', 'rb') as file:
    loaded_model = pickle.load(file)
```

```
In [88]: import pandas as pd

# 'df' is a pandas DataFrame containing my data
df.to_csv('https://raw.githubusercontent.com/Christine971224/Analytics-2023/master/data,
```

```
In [90]: import platform
print(platform.system())
print(platform.release())
```

Windows
10

```
In [91]: import sys
print(sys.version) # Detailed Python version
print(sys.executable)
```

3.9.7 (default, Sep 16 2021, 16:59:28) [MSC v.1916 64 bit (AMD64)]
C:\Users\zhumh\anaconda3\python.exe

```
In [94]: # Dependencies for the project
# pandas==1.1.5
# scikit-learn==0.24.1
# numpy==1.19.5
# pickle-mixin==1.0.2
```